

**the left hand
of data**
designing
education data
for justice

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and
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garcia



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Designing Education Data for Justice

Matthew Berland and Antero Garcia

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Antero would like to say, “Ditto.”

As always, anything you hate about this book is probably the authors’ collective fault, though we both insistently “blame society.”

1

Introduction

Fundamentally, this book is about learning and education. It is about the ways that we use data to shape possible futures of young people as well as the schools, informal learning environments, colleges, libraries, and educational games where these young people interact. It is about the processes by which students are sorted, labeled, categorized, and intervened upon using the bevy of data extracted and collected *from* individuals and groups, whether anonymously or identifiably. When, how, and with what biases are these data collected and utilized? What decisions must educational researchers make around data in an era of high-stakes assessment, surveillance, and rising inequities tied to race, class, gender, and other intersectional factors? And, to the best that we can surmise, how are these complex considerations around data changing in the rapidly evolving world of machine learning, artificial intelligence (AI), and emerging fields of educational data science? These are big questions and not ones typically taken up piecemeal by academic scholarship or in most classrooms with inquiring students. Inspired in part by Gutiérrez and her co-authors (Becker & Gutiérrez, 2022; Keifert et al., 2021), this book strives to understand data in ways that imagine more just futures while building on our existing technologies and knowledge. We can use a speculative

approach that imagines better ways of living alongside data, and this book argues that we need not wait to do better today.

Every day, school systems, educational researchers, and policy-makers at every level of public educational systems make decisions that shape the lives of young people. These are typically called *data-driven decisions*—though whether the data does the driving or if the route was predetermined for particular purposes is a fraught question, largely informed by the political and profit-driven decisions that shape “college and career readiness” models of schooling in the US. Often, the idea of data collection and interpretation spawns visions of university researchers or policy wonks wading knee-deep through spreadsheet sludge to find submerged insight gems. However, for the most part, that is not where or with whom the data live.

Every classroom teacher, principal, and student shapes and is shaped by the educational data that they produce and interpret daily: grades and attendance records are generated; phones emit location data; software tracks student and teacher activity; and so on. Perhaps more importantly, each one of these individuals could likely expound on the myriad ways in which data fails today’s educational system. Data fails school policy decisions. Data fails classroom instructional approaches. Most importantly, data fails the needs of students. Very unlike the popular representation of data science as mainly the purview of tiny teenage ersatz Bill Gateses, educational data is both deeply personal and used by almost everyone up and down administrative chains (Halverson et al., 2007).

As new teachers, we were trained—both formally in a teacher education program and implicitly through how colleagues talked about and categorized their students—to *see* our students through their data. Our teacher education programs encourage new teachers to develop a relational trust with students, but they also ask us to quantify the *who*, *why*, and *what* of all student classroom activity. As much as we see students as curious and questioning individuals, young

people—through the data they create—are implicit quandaries to be diagnosed and *solved*. Schools typically then provide teachers with the tools to treat students as problems ready to be solved. This distancing often prevents teachers from seeing their students as individual identities and bodies participating in the centuries-old experiment of US public education (e.g., D’Ignazio & Klein, 2020).

Throughout this book, we approach the intersections of data, education, play, and social justice through speculative, practical, empirical lens, and critical lenses. All such divisions are necessarily imperfect, but we start this book with an exploration and application of new critical frameworks, then move to chapters in which we use those frameworks to explore how the intersections arise and function in different contexts (e.g., museums, schools, video games). Between those chapters, we offer a series of interludes. These are practical applications of our theoretical perspectives with working program code. If you don’t feel very comfortable reading or writing program code, don’t worry (neither does Antero)! We wrote these to be as accessible as possible, with comments added liberally throughout to allow even avowed nonprogrammers to look at the construction and utilization of data under the hood. The interludes are intended to spark creative hope; with any luck, they will encourage readers to try out, build, and play with practical ideas in ways that enable us to live more just lives.

Schooled Data in Practice

In the high school where Antero taught, at the beginning of each year, every English class would filter through the school’s computer lab in which students would complete a short reading assessment test. Promising “powerful assessment tools” in its marketing materials, the Renaissance Learning Star Reading test is a computer-adaptive diagnostic literacy test. As described on the Renaissance Learning

website (2020), “Star Reading transforms assessment data into action steps for educators, giving teachers helpful insights and tools to strengthen classroom instruction.” In practice, the implementation of this test meant students were asked to complete the assessment over the course of several minutes before shuffling out of the class, when the next set of students would be ushered in for quantification.

By the end of the day, teachers were given a printout with all the scores for their students. The Star Reading test offers multiple kinds of data for interpreting student reading levels, and Antero’s school focused on two columns of data for guiding instructional decisions. Following student names and identification numbers, a column of data elucidated the “grade equivalent” (GE) reading ability for each student. These numbers ranged from 0.0 to 12.9+, denoting the approximate grade level at which students were reading. Notionally, students in an 11th-grade English class would (theoretically) read at an average of an 11th-grade level; in fact, that was not the case. Rather, most of the students in Antero’s classes read at a level “between 4th and 5th grade” (according to the results of the Star test), with some students reading much higher than that but many labeled as much lower.

In a somewhat strange twist of the foundations of sociocultural theory, an additional column was labeled “ZPD” (after “Zone of Proximal Development” from Vygotsky, 1978) and indicated the Star test’s suggested zone of proximal development for each student based on their assessment results. This range was expected to solidify the band of books students could select and read at the school. These paired data points—a student’s GE and ZPD—functioned as the literacy talismans that guided instruction and engagement at the school. In practice, these ZPD scores recast how literacy was seen at the school in literal ways. Every book was affixed with a label designating the band of reading levels that could access it, making clear which books were for whom. The data from this beginning-of-the-year test recast

the landscape of student learning and the instructional materials available to them and—like donning a pair of glasses that may pull the world into focus for some and blur it for others—the Star Reading test reframed how students and teachers were *seeing* school and the books available to students.

The data-created visions of students have social, relational, and affective consequences. For the substantial number of students Antero taught who would achieve second-, third-, and fourth-grade reading levels, the low scores were demoralizing. These tests were expected to function as harsh wake-up calls trumpeting the inadequacies of student abilities. Somehow the students were confronted with the responsibility of raising these scores, even though these students were usually already a decade into the public education system that yielded these results in the first place.

Books with a 2.5 or a 3.0 grade level as part of their range literally look different than books geared at readers of higher ranges. You are familiar with second-grade books: they are picture books; they have colorful images; they have large fonts; and they often are *bigger* than the pocket-sized novels that adults read. They look childish. Telling a teenager to read these books is an instructional moment but likely not for the lessons we are hoping to teach. (The lesson, instead, was a negative “this place/life/work is not for you” or simply, perhaps, “despair.”)

The decades of high-stakes assessment kick-started by the US National Commission on Excellence in Education’s (1983) *A Nation at Risk* report created the chain reaction that yielded the Star Reading test. The Star Reading test illustrates angles on truth in data, interpretation, and responsibility. For example, it is true that the test reflected a clear evaluation of students not reading “well” based on performance data. From the gaze of its creators and from the ways the school used it, the test was not false; it was consistent, repeatable, and clear.

While we can point to policies and educational movements that might have led to the demoralizing feeling of mandating that a 17-year-old read a floppy picture book, this book suggests that data optimized for systems of capitalism will nearly always yield processes that sort and reshape student identities and bodies in similar ways. The drastic ways in which, on a Tuesday morning, sitting in front of a computer for 15 minutes, a student's experience of schooling is recast by a singular assessment, illustrates one of myriad data decisions that students and teachers confront daily. Would the student have been better off without the information? Is there an ethical way to use these data that does not result in a riptide of despair?

Data, its intended use, and the unintended consequences of its collection shape nearly every aspect of how students experience and participate in the world. From the predictive policing algorithms that disproportionately shape the day-to-day, negative interactions that Black and brown youth experience outside of schools to health modification scores that may affect the likelihood of an individual to receive medical care or organ transplants, data-informed decisions extend across everything that we do. Scholars such as Benjamin (2019) suggest that this is but one of the many ways in which market surveillance ideology can manifest racist and sexist histories of oppression within the "normalcy" of daily life.

The ways in which schools use our data only work because we are implicitly convinced that all reasonable options require us to freely proffer all personal information property to private corporations; this is hardly true worldwide. The exceedingly normal feeling today of giving all your data to a Silicon Valley company is part of a grand misdirection. Knowing that from early surveys of colonized land to the present day, approaches to classroom assessments have caused harm, this book builds from an obvious and simple point: *it doesn't have to be like this*.

Data for Speculative Design and Freedom

That said, this is *not* a book which demonizes data analysis. In this book we apply the same kind of critical urgency through which we look at the state of the world. This may indeed be a bleak time when it comes to educational equity, but losing hope is worse than having none. Education is unique in the US in that it is near universal, guided and staffed by people who (whether successful or not) intend good things, and an institution that can genuinely improve lives. In the end, questions for data in education might have come directly from Tolkien (2007).

- Is data science inherently just a Palantir? Does it, by giving you information, stare back at you and, in doing so, doom you?
- Is data science a ring of power, tempting you to use the power of the enemy against that enemy, and, in doing so, becoming the enemy yourself?
- Is it Gollum, an indispensable guide who will help save us, but who can never be trusted?

If the consequences of data collection are demoralizing, ethically wrong-footed, or otherwise lead to pedagogical quagmires, your educational data and analysis are bad. This hardly needs to be said, but the concept of investigation from perceived reality (in other words, data analysis) is a tool that is also leveraged quite often for good and for right (in schools and outside of them). We are, for example, very happy to have vaccines that use data from real human trials; in that vein, we publish papers that use data to expose how to make education or schools better. Rather than focusing on prosecuting the legacies of harm reaped by poor data collection, most of the following chapters look at specific contexts and examples of current data collection. Exploring nuanced approaches to collecting, utilizing, and building from the insights of educational data, we seek to help guide research approaches that preserve and affirm the dignities of participants.

However, before we turn to these contemporary examples in the following chapters, we cast our eye toward data imaginaries, speculative data analysis, and even some real, runnable program code.

Fundamentally, our methodological designs and analytic considerations are informed by dreamt futures. Building on our personal and professional affiliations (in part as self-proclaimed geeks), we find inspiration in some representations of mindful educational data use as depicted in science fiction. We particularly recognize the role of *speculation* as an intentional agentic act informing research, literature, design, and other aspects of life; the imagination of shows like *Star Trek* and the words and worlds of writers like Octavia Butler and Ursula Le Guin mine inequitable pasts to help carve visions of new possibilities shaping data design today. Illustrations in popular media—and promising research we will turn to throughout this book—point in alternative directions. We know we can make the lives of kids better *within* the systems of schooling, but we can also make kids' lives better through *changing* these systems. These are the possibilities of educational data that we might wield as speculative-focused educational researchers, educators, and designers. Until we can imagine just futures that use our data to help us grow, we exist only within otherwise fixed ideologies.

So, who gets to imagine possible educational futures? If it is only the dominant powers of established capital, then they set the space of possibility. To whom can we look for speculative guidance?

Python and Playgrounds

The Python in this book is all runnable online in Google CoLab—something like Google Docs for Python—with no changes from the reader. We have included shortened links here: github.com/mberland/interludes

Indeed, we suggest that you attempt to run all the code and follow the suggestions that are in the code comments, making changes

throughout. That said, you might be asking: What is Python? What are code comments? Why should I run code? What if I do not know how to code? Will this book teach me how to code?

This book will not teach you how to code, we are sorry to say. If you were hoping to pick this book up, read it cover to cover, and then immediately apply for a job as a software engineer at Meta, you are a very hopeful person, and we wish you luck. That said, we hope that by modifying the Python from this book, all nonprogramming readers can make progress toward situating and demystifying code. Though it may look intimidating at first glance, Matthew has written all the code in this book to be generally understandable to most readers and to help illustrate how code intersects with the data it runs.

A short lesson will be unlikely to help massively—honestly, we would just click the links and select “Run all” from the menu—but we can give some context. Python is a computer programming language used by scientists, computer scientists, and programmers worldwide; it is one of the most popular, and it is widely used both by top professionals and in first-year computer programming classes. It is considered to be relatively easy to read—that is, there is not a lot of specialized syntax that would look arcane to a novice. It is designed such that many simple functions can be read out loud to gather their meaning. For example, `print(“hello”)` means to print the text contained within the quotes; in this case, it would print out the word *hello*. The code `# print(“hello”)` would do something very different in Python. It would do literally nothing. Why? That `#` at the beginning of the line marks the line as a “comment”: a note to human people reading the code rather than running code itself. We have peppered all the examples with comments; reading them may help the code make more (or less) sense.

The metaphor for Google CoLab is the “cell,” sort of like a cell in a Microsoft Excel spreadsheet. The cells can contain runnable code, Markdown (human-readable web language), and data, as seen in figure 1.1.

**Figure 1.1**

A cell in Google CoLab.

If you run a cell with Python code in it (typically <Shift-Enter> or <Shift-Return>), it will show the result. There is a Runtime menu at the top of the page under which there exists the option to “Run all”; if you select that, it will run all cells and show you the outputs as they happen. There is a fantastic feature called “Playground mode” which you can get to by selecting “Open in Playground mode” in the File menu. Playground mode does not save changes, so you can change code indiscriminately and with reckless abandon; if it stops working or you just want to start over, just close and reopen the Playground.

This book is much more fun—and significantly louder—if you play with the interludes. It is worth your time, we promise.

The Left Hand of Data

Ursula Le Guin's *Left Hand of Darkness* is, in some sense, about the fundamental disconnect between individualism and the functioning of society. The *mindspeech* (telepathy in which it is impossible to

intentionally lie) casually, maybe offhandedly, topples authoritarianism. However, even in the absence of dissembling, Genly cannot overcome bias in perception of gender and individuality. The book exists as an expression of the idea that there is no justice that is not inherently intersectional, and—crucially for this book—that even “perfect data” reflects the biases of the data collector and analyst. Perhaps ironically (or perhaps cynically), Le Guin’s technocratic society cannot even comprehend collectivist mores. They don’t fit into the schema! The data don’t fit the spreadsheet.

This book is inspired by Le Guin’s book. Our title is a respectful, nonpossessive reference to the book as well as a (perhaps oblique) reference to *Star Trek*’s Lt. Commander Data, who contains a button hidden in a fingernail of his left hand that serves as a sort of fail-safe for changing the narrative (per Bowman, 1990). Data has an evil twin brother, Lore, who also contains a hidden button on his left hand. The story arc between these two brothers posits the idea that “lore” (i.e., narrative) and “data” (i.e., evidence) are mirrors of each other, but that they must “forgive” each other to be whole. The relationship between what seems like hard evidence (but is, instead, a person with perspective) and what seems like unmoored bias (but turns out to be quite calculating) is precisely one of the dialectics that this book foregrounds.

Data Imaginaries in Urgent Times

We write this at the crest of one of many waves that seems to be plunging the US further into the icy shock of economic depression, social upheaval, and political discombobulation. We started writing this book just before the COVID-19 pandemic. However, the past few years have pulled into focus the urgency for the heuristics at the center of this book. Ongoing upheaval at local and global levels is generating new capitalist demands for schools to measure, sort, and judge

the validity of forms of knowledge and intelligences. These systems are and will continue to be sexist, racist, transphobic, homophobic, ableist, and engaged in other discourses of oppression.

Though this book does not focus solely on race, its investments in racial equity are never far from the surface. There are fundamental questions that the construction of race in the US poses to every educational endeavor: Are you making things better for people who have been systematically oppressed? With whom are you surfacing the development of your work, and how do historically marginalized individuals shape and co-construct this process? Of course, there is value in helping every child, but every new generation of researchers seems to find that when they do not keep antiracism as a core goal (and sometimes even when they do), they will likely just make the situation worse. Throughout the book, we attempt to foreground both how mechanisms of oppression function and possible modes of resistance to those mechanisms. It is not enough, but it is what we can do.

There are some sets of arguments—not unfounded—which claim that any use of quantitative data is dehumanizing and will, in some way, *ipso facto* result in racist outcomes. This implies that data science possesses a unique dehumanizing power; however, this argument misses the fact that data collection is just one of many mechanisms of power, which seek to dehumanize and control populations (e.g., Foucault, 1977). In the absence of spreadsheets, for example, power operates through religion, capital, and other sociopolitical institutions. We can design different futures through reappropriating existing tools. In fact, the current educational moment demands new ways of thinking about the future of education. In the spring of 2020, there was an unanticipated, widespread pivot to using distance-based teaching. Improbably, this educational response to a pandemic was even more bleak than the futures envisioned in dystopian novels, films, and videogames. For many schools, what became the essential task—the absolute core—was distributing content into the void

rather than supporting children. Many districts could not account for the location or physical safety of their students. The models of instructional delivery taken up by schools provided little agency, little care, little interaction, little collaboration, and no equity. During months of heightened anxiety and social distancing, schools could have played prominent roles as bulwarks for community healing and growth. Of course, such possibilities were hardly considered and this lack of action or imagination falls on educational leaders, politicians, researchers, and educators writ large. This lack of responsiveness to a world beset by trauma was only exacerbated in the months following nationwide sheltering in place. The onset of the COVID-19 pandemic was rapidly followed by an overdue collective response to systemic antiblackness and racism within the US. In both health crises, young people in the US were left alone: coping, fearing, and mourning a country rattled to its foundations. This is not a valid future of school.

Feeling the walls of the unlit room of the present moment, educators, parents, politicians, and researchers are looking for new ways to *do* schooling. Recent attempts have not been particularly promising. Studies of massive open online courses (MOOCs) suggest that they—especially ones that are not strictly synchronous—do not fulfill the dream of an equitable future or a great equalizer; in fact, they may be undermining it (Breslow et al., 2013; Reich & Ruipérez-Valiente, 2019). In the context of MOOCs and in current forms of distance learning, it may be worse for many kids to attend these schools than to simply not go at all—even considering exclusively school-based academics.

The chapters that follow map out some potential digital futures that have equitable implications. We write this hoping that educational researchers might use the ideas here as propulsive momentum toward better possibilities obscured in the smog of toxic policies. Though we would like to offer a blueprint for liberation, that task falls outside of the purview of this book. Rather, by taking seriously the expectations

about, with, and through data, our speculative approach seeks to redefine how we work within rigid systems and how to creatively resist or undermine them when necessary.

Recognizing the urgency of these present times and the decades of inaction that they have been met by, these chapters are written to support the needs and growing concerns of the angry parent, the angry educational researcher, the angry teacher, the angry principal. But they go beyond that, too. We are writing, in this moment of myriad threats leveled at the most vulnerable in the US, to meet the vision and courage of the *hopeful* parent, the *hopeful* educational researcher, the *hopeful* teacher, the *hopeful* principal. If you are a researcher who works toward a commitment that school should build from a foundation of equitable learning futures, that school should support and nurture every child, and that school is not simply a penitentiary from which people distribute content, this book is for you.

2

The Anonymity Spectrum

Regardless of where you reside within the academy, if you are involved closely in the field of educational research you will have had to contend with sorting your work into methodological buckets. Are you, for instance, a quantitative researcher focused on large-scale samples of educational phenomena? Are you, instead, a qualitative researcher seeking to explore nuances of phenomena that eschew counting and numeracy? Or maybe you present yourself as the ever-elusive mixed-methods scholar, likely with heavier leanings toward one methodological paradigm than another, but aspirational in walking the straight and narrow of both approaches regardless. The factions of methodological work are important, but they often take up so much of our imagination as a field that it could be easy for early career members of the educational research community to see these factions as the primary means of understanding what you do and—worse—*why*.

But let's set aside any qualitative-vs.-quantitative feuding. It has gotten in the way of a better understanding of the data we harvest from the sowing of educational futures. As one possibility, we (Matthew and Antero) have been wondering what our research efforts might look like if we centered an understanding of how our data come to know the individuals and groups they target and how our

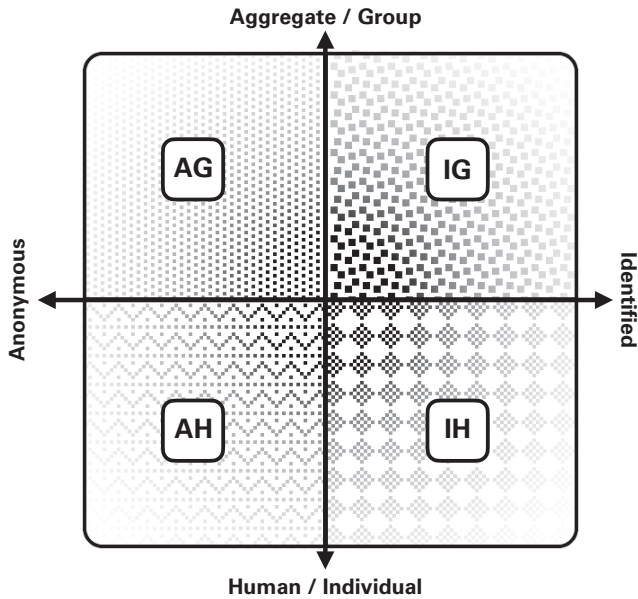


Figure 2.1
AnSpec (the Anonymity Spectrum).

data align with the outcomes of research processes. Thus, this chapter proposes a lens on data and education through which we can see a spectrum of design and interpretive possibilities in education, which we will call AnSpec (short for ANonymity SPECtrum). AnSpec is a two-dimensional space, as shown in figure 2.1. It allows us—as researchers, educators, and varied stakeholders invested in the lives of learners—to make intentional decisions about and with data that comprise various aspects of how we understand people: wholly, individually, specifically, and broadly. Organized across four quadrants, this spectrum helps elucidate the degree to which data are found within the range from anonymity to identifiability and from aggregated (“grouped”) to individualized.

It is important for us to critique these axes. Why these specific axes? What do these axes erase? What values are implicit in these axes? What do they say about culture, history, or power? There

are many ways of approaching the goals of an intervention, of a design, of a collection of numbers; AnSpec pulls into focus considerations of design and biases of data that are regularly overlooked or backgrounded in the design process. These axes represent an extant discourse; it is (necessarily) not the best possible discourse. Over the course of this book, we will both return to AnSpec as a lens and problematize it as a tool.

We can find numerous examples—which we refer to throughout the rest of this book—that exist along the outer bounds of the space. Large quantitative data sets and microanalytic qualitative studies parade the affordances of data along the periphery of this spectrum. Antero's ethnographic work often attempts to attain an $n = 1$ approach to data, getting as close as possible (which usually makes such data very identifiable as well). In the same way that we could map our own research into a few general clusters on this methodological map, we want to recognize that this is by no means a definitive reflection of current research practices. By no means are we arguing that AnSpec is the *best* representation of possible discourses for data, or for modeling data and privacy in education. Rather, this is one approach at *seeing* what is occurring from a vantage point not often perched upon within our fields.

So, what is the value?

Education and education research frequently background the decisions that AnSpec highlights: *Why* is a study collecting anonymous, grouped data? Why do studies about individualized student performance (like the Star test administered in Antero's classroom) build from and toward specific assumptions about student achievement? Alternatively, how might we understand the ongoing "reading wars" that have shaped US literacy education models for decades (e.g., Pearson, 2004) if the values imbued in these different stances were mapped across AnSpec?

Corpora (that is, large data sets) carry unspoken rationales. In this sense, rather than further endorse dominant modes of data

collection, AnSpec functions to critique and analyze existing data sets and to facilitate more purposeful data decisions in our scholarship moving forward. As we explore the possibilities of data for transforming educational systems and contexts, we need to admit that—even when we are wary of blind faith in algorithms and their authors—we are drawn to the potential of using logged data to support people in learning and schooling. At the same time, educators, researchers, and the public today tend to use the term *data* with enough vague hand-waving as to render the term meaningless. As Hume (2007) suggested, what we take as evidence is not defined by abstract reason but instead by whatever habits we use to support our arguments. The evidence—or “data”—can be evaluated, analyzed, and (mis-)used from any perspective or framework; any understanding of data is an appeal to habits and mores. In the rest of this book, we write with a more familiar sense of *data* as “numbers generated about a person.” This is made more complicated by the fact that anything encoded digitally—which is to say, almost all the modern world—is encoded numerically. That observation is not a “gotcha” or an idle notion. As computing power has grown, phenomena that seemed relatively resistant to “data analysis” (e.g., essays, photographs, scents) have become so obviously numeric so quickly that it is sometimes a surprise to find them in a purely analog form within an organization such as a school or business. The quantization of data is inherently reductive, but so are words, images, and thoughts. Any perspective is a limited perspective.

A myriad of research considerations, protocols, and workshops are offered and sold to interested and frustrated scholars, educators, and policy analysts alike. Does the world of justice-driven education research *really* need another framework for interpretation? Not necessarily! However, we suggest that what separates AnSpec from other approaches is how its design centers the possibilities of *what if* while acknowledging the horizons and limitations of what we do (or don’t)

see as we conduct our research. We must acknowledge the humanity at the center of research. AnSpec seeks to reorient some of our scholarly practices around the *whom* and the *what for* of our work. Clearly, we will be exploring research applications across the four quadrants of the spectrum in substantial detail in the pages that follow. However, we first label and describe our axes here.

Complexifying Anonymity: The Axis of Identification

When we think of our personal information as data, it is worth asking what about us is being identified. Who are we? In daily life, we may range from being uncomfortable giving our last name (to, say, an unknown caller) to filling out a form with security questions that require information about a pet or favorite aunt. Often, these two responses may well be given to the same company in different forms. In fact, Matthew had a bad experience canceling a gym membership in the past, so when he signed up for a new gym, he went so far as to pay for it with a burner card. (This card maneuver did not help when he finally canceled this membership.)

Identification is a mode of specificity about personal information, even when flexible and contextual. Goffman (1974) shows that “who we are” is contingent on the “frame” in which we find ourselves. Sometimes we are parents, sometimes we are professors, sometimes we are really bad at sports. These identities are not all simultaneously enacted when one of us plays a video game online, though they undoubtedly affect our behaviors. Indeed, the inflexibility of identificatory data is a growing issue. If, for example, marketing algorithms infer that you are a mom, you will likely stop receiving “dad” or “nonparent” shopping suggestions.¹

Identification is a range, and there are tiers to it: some identity data are effectively irrevocable. You must really trust someone to be willing

to give them your bank account information or Social Security Number. If you choose to do so, your life may be further shaped by that decision. Perhaps you are bankrupt now? (We hope not.) Perhaps you've revealed sensitive information about yourself in one situation (if you are pregnant, disabled, or economically disadvantaged, for example) that found its way to a university institutional review board or potential employer. Or perhaps inferences based upon your browsing and shopping histories delivered incorrect information to third parties. Often the identifications made about you are wrong. They are automatically inferred based on statistics. Anecdotally, Matthew knows a woman in her seventies whom an ad network has labeled a man in his thirties. (This is likely due to her love of first-person-shooter video games.) These identificatory labels are typically not factually incorrect on average—indeed, a lot of financial investment goes into making them “correct enough” for sales and marketing purposes—but, unsurprisingly for a regression to the mean, they consistently tend toward the (pre-)dominant population. The central limit theorem abides. If 97 percent of people who play game X are verified as men, then, without further information, almost any algorithm that uses those data will decide that, if you choose to play this game, you are probably a man. Gender scholars—and millions of others—have broken down these dichotomies and demonstrated the complexities of gender as a construct (e.g., Butler, 2002), but most marketing algorithms do not care who you are so much as how you will generate money. Indeed, if you are willing to buy what the other 97 percent of people labeled as “men” are also buying, you, to this algorithm, are an “effectively-a-man”: gender, in this case, is a marketing construct.

If the labeling largely occurs on the tail end of an algorithm's determinants in various social contexts today, the axis of identification is moved toward the agentic process of supporting people in controlling how they might be identified or valued in research contexts. We then have four nonoverlapping categories: 1) how *you* care about yourself as a person; 2) how others care about you as a person; 3)

how researchers or educators understand you as a person; and 4) how the data have constructed you. *As such, we consider identity data to be the set of characteristics, labels, information, or behaviors drawn from you and/or applied to you.*

Importantly, identity data changes quickly. What is not identifiable today may be identifiable tomorrow. For instance, people often use “voice” as an identity characteristic when we are physically proximal to each other. If a loved one calls our name, we often know who it is. Computers do not typically, at least at this time, register this type of identity characteristic. Though it seems as if voices are not so obviously unique at a global scale, there is no apparent reason to believe that they will not be identifiable someday soon. What counts as identity data today? What counted yesterday? What will count tomorrow? We will come back to these questions as we progress through the book.

Complexifying Individuals: The Axis of Aggregation

If data on one person are individualized, then data about multiple people are called *aggregated data*. That said, the concept of aggregation (or “grouping”) contains obvious gradations. A group of two people (“Emma” and “Alexander”) exists more or less only at the personal identity level: we can ask questions about them such as “What are your names? Where are y’all from?” and get answers that anyone who speaks the same language can understand. Scaling that up to a global level is absurd. What does it mean to name seven billion people? You could not feasibly hear every name even if you spent your entire life listening. That said, the group of Emma and Alexander and the group of “Humans on Earth” are both aggregations of a sort.

Aggregating at the level of groups—*stamp collectors, women, humans, those who have just broken the vase*—carries serious sociopolitical implications, but every model of cognition and every algorithm requires

some level of abstraction. That is, aggregation is abstraction; Quine (2013) suggested that it is, in part, the naming itself that brings things into being as an object of consciousness. Similarly, we unconsciously group people by any number of their characteristics such as their appearance, behavior, and our prior experiences with them. Cognitive load theory roughly suggests that we can only keep a few things “in mind” at a given time: if we see twenty people, we have grouped them into fewer than ten categories, whether we like it or not.

This kind of cognitive grouping (or aggregation) happens, quite literally, always. While the bar for “perceptible features our mind might care about” would be much lower in a lightless, silent, odorless room than, say, Times Square, no matter where you are or what you are doing, there are more than ten features perceptible to your mind. Algorithms are built by conscious humans trying to solve problems, and their grouping schemes will often look much more like dominant, labeled grouping schemes (e.g., race, language, and gender) than we might expect. As suggested so eloquently by Noble (2018), algorithms cause action in the world based on these grouping schemes. Everything from social media to school to marketing to predictive policing rely on human-cognition-scale groupings, and it is humans who must parse the results. Matthew’s videogame-loving acquaintance in her seventies will be offered advertisements for consumable goods that would be unsuited to her, such as student loan debt consolidation (not to suggest that she couldn’t go back to school for another doctorate!). That said, there are statistical regularities to these explicit, demographic groups: Black people have been systematically oppressed contingent to their identification as Black, so Black may be a relevant and just category to consider, and/or it may just encode and reinforce racial bias. Due to that aggregation-oppression, Black Americans have been systematically barred from many opportunities. A relatively simplistic (and broadly unhelpful) response from many companies has been to aggregate in ways that do not lend themselves easily to human-comprehensible labels—or at least

not to *report* those labels, so they do not report how they are replicating oppression. However, ontogeny recapitulates phylogeny; that is to say, the ways that things come into being are manifested in the ways that they act in the world. It is a trick, therefore, to pretend that when we aggregate without using political terms, we can avoid racism. (This is sometimes called “race evasiveness,” per Annamma et al., 2017.) For instance, one may avoid using explicit racial/ethnic categories (such as Black) but substitute, for instance, users of specific personal care products designed for Black communities. It becomes clear that if we are not conscious about how we are replicating oppression, and actively keep working to counter that, we are almost certainly going to replicate the oppression. Hiding it in black boxes does not help; it hurts. So, the thorny question remains! We will aggregate—our brains do not allow otherwise. But how do we aggregate without recapitulating systemic oppression?

One answer is to make a conscious point to notice instances of systemic racism and actively confront that racism to whatever degree possible (per Kendi, 2019, for example). Rather than letting statistical aggregation find the “best fit” labels, we evaluate situations for the potential effects of bias, apply explicit labels, and try to mitigate or even reverse historical damage. Data are still required for this evaluation, but the act of aggregation or disaggregation itself becomes a political act.

We consider aggregated data to be data that groups people.

Identification and aggregation are rarely independent of one another. Indeed, their interaction produces a variety of unlikely results, some of which we will discuss later in this book. The rest of this chapter offers a quadrant-by-quadrant tour of AnSpec, while much of the rest of this book explores specific, applied examples of how AnSpec shapes contexts of learning, research design, and analysis. In the rest of this chapter, we focus on behaviors and characteristics of clustered data.

The Four Quadrants of AnSpec

Referring to figure 2.1, the four quadrants of AnSpec are named after the general areas that are represented. However, we want to re-emphasize that AnSpec is not a pair of binaries. While data can be imagined as either anonymous or identified and individual or aggregate, there are degrees to all of these considerations, and it is this indeterminacy that helps elucidate reimagined contexts and opportunities for design.

Anonymous Grouped Data

Anonymous Grouped (AG) data are those data that are purely anonymous and always exist in aggregate. An example of AG data is the data collected from a traffic counter: one of those strips that lies across a road and counts the number of wheels that roll over it. It is typically difficult (or even impossible) to identify any specifics about the individual humans who generated these data. One cannot guess their names, addresses, or, really, anything except for the most general possible information about whether they drove over a traffic counter in the middle of a city. It is possible that these individuals do not even live or work in the city, depending on the location of the traffic counter. Perhaps you know some external information about the socioeconomic status or cultural background of people who live in the neighborhood, but nothing about the data itself would be enough to identify anyone.

Often, AG tasks require local information that requires little contextualized information; if you are a potato seller and people in your town start eating 500 potatoes a day, you do not need to know much about those people, but you know that you should buy more potatoes. In the case of the traffic data, it is rare that one would use an individual line of these data for much, as it would mostly just read “a wheel went over me at time X” and, given that tractor trailers exist

(which have many more wheels per vehicle than your typical family car), one might not even be able to estimate the number of vehicles, depending on the specific path. Despite the anonymity, these kinds of data can make lasting changes on the landscape of education, as we'll continue to explore.

AG data currently affect how we use data for learning and will continue to do so in the future. One nice example of the use of AG data for learning environments is the example of a room at the British Museum (in Savoy et al., 2014). To better understand what to highlight, the museum wanted data about who was perusing which exhibits. Unfortunately, the data from the exhibit itself was minimal, and they collected location data at the broadest level: how much do people walk through or stand in each spot? Taken at an individual level, such data are nonsensical; there is not an obvious reason to make it identifiable. However, at the aggregate level, the data helped the museum identify a fundamental misstep in spatial design. The data about visitor walking paths revealed that visitors were frequently missing a whole chunk of space in the exhibit. What's more, while walking through the space, visitors often even failed to see that they were missing a set of exhibits, depending on the angle to which they were walking into the space. By using the pathing data, the museum found that, with some relatively minimal rearrangement, they could enable people to see all the exhibits. The museum's analysis of location-tracking and path-tracking data highlight some potentially beneficial applications for AG data in educational contexts.²

Corporations also use AG data extensively. One example is a classic "A/B test," in which one group ("A") gets one form of the software relatively invisibly, and another group ("B") gets a close contrast case. This is one of the most common forms of testing for software companies, and these tests tend to be anonymous and grouped. Most large online retailers reportedly require A/B tests for every public-facing minor change to their sites—even just a simple wording change in

the middle of a license agreement. Google has probably tested you today: you may have searched, and a link was almost imperceptibly shorter or longer. If tested on enough people (~100 million, perhaps), they can decide if this nearly imperceptible difference produced any meaningful change in user behavior, such as clicking on an ad or spending more time with a site. Because these corporations are testing at a global scale, anonymity is effectively assured; they could not care less if you, in particular, clicked on an ad in this A/B test, as the difference may be 0.001 percent or less between the two groups, or the difference may be a couple of milliseconds of load time on average; however, these small differences may still translate into millions of dollars in profit over the life of that button. At a much smaller scale with more contrasts, similar A/B tests are at work across education, especially when it comes to educational technologies. Large ed-tech companies routinely analyze Web traffic, currently an evergreen resource for AG data. AG A/B tests would seem to be broadly neutral (or even good); as we will discuss later regarding anonymous individualized data, however, A/B tests at scale are not inherently innocent.

Popular sentiment today suggests that people are often resistant to having their location tracked. A general allergy to surveillance—anonymous or individualized—is perfectly healthy; the authors share this affliction. However, in situations with AG location data, such methods may be harmless. Making students and other users aware that their data is being collected or tracked is an ethical consideration that differs greatly depending on whether a notification is in the pages-long gibberish of a digital user agreement, part of a complicated protocol for an institutional review board, or ignored entirely by a municipal worker placing a traffic counter on a road in a nearby development area.

This is not to say that all data uses require complex technology such as location tracking: for example, schools often decide to replace a set of textbooks based on which ones have been thrown away or have gone missing. Assuming that such accounting of books

lives in some administrator's Excel sheet, over time such information becomes grouped and anonymous logged data. The changing nature of information over its lifespan means that data may move from one quadrant to another.

Identifiable Grouped Data

Identifiable Grouped (IG) data, such as surveys and polls, are a common form of mass data collection. Most of these data are only valuable at scale. The census is, perhaps, the most canonical example: census data are detailed and specific enough that any single line of the data would likely be sufficient to identify an individual. Information such as address, zip code, telephone number, name, age, and income level are grouped for analysis, but exist at an identifiable level.

IG data are, somehow, both dangerous and anodyne. Improbably quoting Stalin while ruminating on both COVID-19 and *The Fast & the Furious* film franchise, a ten-year-old recently said to Matthew, "A single death is a tragedy, a million deaths is a number." The fact that this quote survived (filtered) through a grade-school classroom shows the power of IG data. Indeed, identifiable grouping is wielded by entities like the US's Immigration and Customs Enforcement (ICE) in justifying the rounding-up and imprisonment of people. Sources of such data do not allow for understanding individuals, only for categorization and, often, weaponization.

Let's be clear: demographers are not evil by trade, and, without clear data on who is where, doing what, we have radically impoverished (and presumably dominance-biased) views of the world. Governments that recognize the power of their populace and the diversity of identity can address and support that identity as much as target it. The potential for IG data to uplift as well as to oppress depends on the nature of the questions being asked, the purposes of data collection, and the autonomy and agency of the organization at the center of such work. A government census, for instance, can

wholly exclude or bring in nuanced perspectives of a country and how it should be organized.

However, there is something quite powerful about undermining the IG nature of data. There is (or was) a Twitter account (Zhang, 2015) that attempts to humanize the census, and it is quite powerful and revealing. Making clear the actual individuals who are at the heart of each entry in the US census, the account reframes viewers' interpretations of what politicians talk about when lumping individuals into broad categories. A sample tweet: "I worked less than half of last year. I studied civil engineering. I moved last year. My commute is 12 mins long. I drive by myself."³ There is an unmistakably sad tone to these tweets, though they simply report the public data from the census. By humanizing a single line of data, the data that a census collects makes each individual into a story—a movement toward disaggregation.

IG data powers most advertisements we see, both offline and online. A company wanting to advertise on Facebook, say, picks sets of demographic categories ("commute less than 20 minutes" or "African-American") and ads are sent to the feeds that match those demographic categories. Users of Facebook must trust Facebook (or be unbothered by *not trusting* Facebook) with their specific demographic and individual information, presumably with the hope that their data are somewhat aggregated so that advertisers do not just show up at their house and attempt to sell them T-shirts, fertility monitors, or machine-washable shoes. In short, IG data are everywhere, and they contain within themselves their contradiction: the gloss of aggregation emotionally enables us to give identifiable information under the (potentially mistaken) belief that we are not then personally identifiable.

Identifiable Individualized Data

Identifiable individualized ("IH" for Individual Human) data are data about individuals: your social security number, your demographics, your name and address, your grades, your family members. These

data can do immense good or immense evil, and they are a powerful tool. The tradeoffs for IH data might seem reasonably obvious to many readers; they exist as a function of trust. There are things that identify you that you should (and probably do) only tell your partner, children, or parents. Very few people give their social security number out freely. In fact, it makes national headlines when people do this: the *New York Times* reported in 2008 that when the owner of an identity fraud service named “LifeLock” did this, his account was hacked within days.

A major question of IH data revolves around what “counts” as purely IH data. Do you give your name and address freely? Matthew gave his name, address, and phone number to a cable company representative recently, knowing that his privilege as an adult cis-het man endows him with a smaller set of identities to be exploited—he is treated as a “default.” We have had family members targeted for harassment simply for being educated women online, colleagues targeted for being Black online, and friends doxxed for expressing what-should-be-uncontentious views (such as “kids dying in school shootings is a bad thing that happens”). Sharing IH data is fraught, and it means something different to many people, just as “identity” does. Obviously, “being Black” and “being a birdwatcher” exist at different levels and modes of identity, but both may serve as identifying or sensitive if they can be tied to behaviors. Do you want people to find you and exploit the triangulation of your data?

IH data serves as a nexus of how the power relations that govern society and culture at large come to impinge on the agency of the individuals within it. It is too often used to consolidate power in existing aggregations. That is, power and capital tend toward individualizing an already powerful white man while marginalizing most others.

Anonymous Individualized Data

Anonymous individualized (“AH” for Anonymous Human) data are those data through which there is effectively no possibility of finding any identifiable information about a person, but the situation

or data could lead to changes for that person. For instance, when you select “no dairy” for the menu at a wonderful restaurant, Clover, in Cambridge, MA, the information is logged and the menu is adapted to fit these specific needs. Many videogames use such data extensively. It is hard to determine someone’s name or address or many meaningful features about them based on how they play a game like Tetris, but the game can adapt to their specific play style; for instance, the game might drop the T block more often or less often based on how often it is part of a successful Tetris.

AH data is useful in our quest to try to implement just data analyses, but it has a core weakness: it is inherently unstable. The more AH data one collects, the more it tends to transform into IH data: by triangulating seemingly innocuous or opaque data, you can often learn a lot about something or someone. Classen et al. (2015) were able to identify individuals by vibrations on windows; Zeng et al. (2010) were able to identify individuals simply by evaluating how long it takes for their web searches to finish loading. Data are rarely perfectly “clean”; rather, they bring along the detritus of ancillary information. Over time and with different lenses, data that once lived in one AnSpec quadrant metamorphosizes; the AH caterpillar may balloon into an IH butterfly, given the unsuspecting tools or contexts. Often, you can jettison or avoid some ancillary information, but it’s rare that companies, for instance, would want to jettison those data, or that one could prevent the slide toward identifiability. This slide is one we will continue to explore in the next chapters.

Limitations and Missing Axes

The quadrants in AnSpec bleed into one another. Because our contexts shape how our information becomes legible to different algorithms, these axes become unfixed in time and space. Such are some of the key limitations inherent in each of these quadrants.

The processes of quantization are essentializing processes. Knowing that data vary in quality, quantity, type, and structure, the AnSpec framework is a starting place for outlining how individuals are valued (literally and symbolically) in our work as educational researchers. Through essentializing data, what features do we keep? What is foregrounded? What is backgrounded? Indeed, does the quantization of human experience itself inherently reduce the human experience? To say “yes” would be a simple denial of the last few centuries, but some days that may not be such a terrible thing. In the next two parts of this book, we will explore relationships among data, security, and justice; play through examples, applications, and code; and practice using AnSpec as a tool. We will attempt to frame justice as a process and an orientation rather than an example of our nifty tool, but it is incumbent on all of us to keep that in mind.

3

AnSpec Research Methodologies

We should probably just let kids be in charge of our methodological dreaming. Talk to any toddler long enough and what you'll get is a bubbling mixture of off-hand observations ("Daddy was grumpy, I ate some strawberries, that doggy's name is Olive") alongside playful innovations ("this [invisible creature] is my anteater named Squeak, would you like some of the mango ice cream I just made out of bark and fortitude, I bought this spaceship from Costco"). This stream is nonrandom data, all carrying personal information for a rapidly developing brain and an individual's agency enacted through possible play states. The bid to take an imaginary ice cream or to pet a (usually friendly) invisible anteater: these are the attempts at finding the boundaries of what's possible, what's permissible, and what the rest of the (usually adult) world deems impossible. It is in these attempts when the bids for new forms of play are discarded—a phenomenon that is itself a point of data collection for children—that students discover the rote methods of mundane life within which we are expected to comport our bodies and minds.

Perhaps contrary to the ornery nature of some parts of the opening chapters of this book, we do not *blame* data for the myriad problems plaguing education and educational research. Rather, we point

to the lack of imagination around what data are possible or what tools might be expanded as collectors of data that are overlooked or deemed otherwise impossible.

Education is a space of intentional praxis. We say this knowing that the word *praxis* is bandied about too often. For us, the marriage of theory and practice means taking the key speculative component of this book—an AnSpec framework—and working toward practical applications in formal and informal learning environments. There are very few theoreticians of education who do not also teach and/or learn; most of those people presumably at least consider their own theories when trying to teach and learn. It is unlikely that you will find many, say, constructionists teaching gigantic lecture classes with high-stakes testing and weekly quizzes. (Complicating the situation, however, is the fact that many people have jobs that ask them to do things with which they do not agree.)

This street goes both ways for many of those theoreticians: many (if not most) educational researchers would like to understand how they might teach more effectively, learn more efficiently, or improve their own schools. Many fields are united by a subject matter, but education is slightly different, as the only agreed-upon category definitions are unacceptably broad—“human betterment but not in a medical sense” or something that might also feasibly contain all the arts or “school stuff”—which could also contain land management, real estate, and payroll.

If *education* encompasses everything from the nuances of flower pressing to mastering the art of real estate management, then *learning* might be slightly more specific: becoming more able to do or understand something. I am more able to pound a nail with a hammer than I am with my hand—I could not get the nail in without the hammer. Is that learning?

Regardless, figuring out how to use a hammer is closer to what you or I probably mean by *learning* than *education* is to “having a good day.”

Fittingly, the diversity of the definitions for terms such as *education* and *learning* also supports a similarly broad variety of research methodologies. In this chapter, we outline how one might use AnSpec and the lens(es) of play, data, and justice in research across critical, theoretical, empirical, and design perspectives. For the purposes of the chapter, we define *learning* as “coming to understand how to do or make something new across multiple contexts” (and we will, mercifully, avoid any unpacking of the words *do* and *make* here). *Education* is broadly defined here as “the schooling that foregrounds teaching and learning.” These are not particularly useful as *universal* definitions, but they give us something from which to work.

As a “way of seeing,” a lens can help pull particular aspects of the world around us into focus (Berger, 2008). Salient to the aims of this chapter, AnSpec as a lens provides us with a connected set of features to foreground, such as anonymity, cooperation, and agency. So, what happens if one uses AnSpec as a lens on something as simple as a chair?

Here is an exercise: Use AnSpec as a lens to study the chair you are currently sitting in. How do anonymity and aggregation interact in, around, from, and through your chair? If you are not sitting in a chair, you are explicitly exempt from the assignment, but couches are chairs now. (Here’s the part where you stop reading for a second, groan audibly at the suggestion that you must break your concentration and either close your eyes and think for 20 seconds or feel a twinge of guilt in convincing yourself that you will come back to it.)

Here’s a stab at one author’s chair: the memory foam, heat signature, and limited number of people with access to the chair make it easy to fully identify the last occupant. That said, the more people who use the chair, the less identifiable those data become. If, for example, two or more adults have had access to the chair before you, it is unlikely that you, lacking proper instruments and expertise, would be able to identify who sat in it, the order or duration in which they sat it in, or the amount of time each person spent in the chair. That is, the

chair, with or without an AnSpec lens, tells me relatively little about education and/or learning. (This makes it even more unfortunate that some people measure students' behavior—and thus grades—by how long and how still they can sit in a chair.)

So, how do we *study* education and learning outside of chairs? What would it mean to see them through the AnSpec lens?

As with a lot of research methods, the fundamental questions come down to: “What are you trying to ‘solve’? What are you trying to understand? What is the problem?” If we’re trying to understand how to see education and learning through the lenses of play data and justice, we might need to figure out what an end goal would be. What is the value of the research? If the research does not hold value for anyone other than the researcher, it is not research.

Question 1: What Problem Are We Trying to Solve?

If successful, this book will enable readers to generate creative solutions on how to use data ethically in education. Let’s say we are trying to design a system that supports people in understanding which data they are giving to, say, Social Media Company H (SMH, for short). Why would we do this? Is this a problem that would be solved by exposing the data? It is trivially true that relatively few people feel that exposing personal data comes at a personal cost. It may be that people see exactly what they are giving to SMH, and their reaction is to think: “that seems like a fair trade to receive a free service that I use daily.” Does the act of creating a tool that exposes them to their data imply that: 1) they should not feel that way; 2) there is something implicitly “wrong” or “evil” about the trade; or 3) we assume they have no idea about what data are sent to SMH?

A quick aside with some details blurred: Matthew was talking to a developer—I will call them “Space Ghost”—at a popular social media entity when it became public that they only offered “posts” that

“maximized engagement.” That is, the system put people in a bubble and was stoking impotent rage on purpose, and these things corresponded to attention and clicks (i.e., money). Space Ghost was legitimately surprised that this was not common knowledge, as were most of their friends at the company. They said, “What do people think we do for a living?” This was a private conversation with a friend, and they were not feigning naiveté. They literally could not understand how people could conceive of or rationalize free receipt of the service as *not* being about getting views that lead to ads. In this case, the design of the tool was done from a different angle of bias but was conscious of that bias. They wanted to maximize ad views—this was the problem to solve—and the theory makes it clear that emotion leads to more ad views, and that the more emotion (positive or negative) that was elicited, the more ad views the company would receive. Rarely in research on learning or education is the target so clear or the consequences judged irrelevant.

Question 2: Can the Learners Make Meaningful Decisions?

The bases for learning any content often hinge on two core questions: 1. Is there manifest value in learning the content? 2. If so, how can the learner see that value in the content? Then there is another question: 3. What role do learners play in deciding whether and how they see or use that value?

It may be the case that our learners do not see obvious value in understanding the flow of their personal data; it may be the case that they are correct not to see that value. It is, perhaps, the case, as we suggested earlier, that they have made the decision that the trade of data for functionality is a good one. Can those students *not* engage in the activity? Should they be able to avoid engagement? We rarely force adults to learn some specific content, and there are very few mechanisms to do that.

Let's say it is possible to convince a group of learners of the value of the activity. (That is not always particularly hard.) Can they make decisions in the activity that are meaningful for them? Can they make choices that affect the activity going forward? Simply submitting information to a teacher—while very common in traditional schooling—tends to feel bad to most people. Can people make decisions about the consequences of their actions? Decisions in life—even minor ones—have some short-term consequences, whether it's a simple, conscious decision ("eating makes me less hungry") or something more implicit (looking up $\Rightarrow$ a tree is seen).

How can we ensure that we are respecting the agency of our learners? The basic tasks of research are important here: we must ask people, listen to them, and see what they do when given the chance.

That said, asking them is often insufficient, and there are conditions in most schools for specific answers. One way to get those answers might be to look for the relationship between their decisions and the way that they interact with the consequences of those decisions. In our activity, we might try to verify that many possible activity-based decisions are being made by students in ways such that they invest time in the consequences of those decisions.

In life, we often try to evaluate our *own* engagement by how much and how well we create habits. If we do not go to the gym every day, despite saying that we want to go to the gym every day, we do not assume that we are engaging in "gym life" *in absentia*. That said, if we do not take some time to evaluate the possible set of decisions and options, we will almost certainly commit to something in which we do not want to be deeply engaged (maybe cycling is more engaging for you than weightlifting, but you would need to have tried both, perhaps). It's a tricky balance.

In Berland et al. (2013), we propose a name for this pattern: EXTIRE. EXTIRE stands for exploration, tinkering, and refinement; it implies some commitment and some manifest agency on the part of the learner. Something like EXTIRE is simply part of "see what they do

when given the chance.” That is, when you are learning something new that is complicated, one particularly productive trajectory is first exploring the space (e.g., trying all the different weight machines at the gym for less than a minute), then tinkering (e.g., settling on a few for an extended amount of time, and then trying out changes in the various ways that you interact with them), and finally refining (e.g., settling on a single machine and engaging in some focused way to improve your form).

Question 3: How Do We See Our Own Bias in Designing, Developing, and Deploying a DBR Learning Environment?

Design-based research (DBR) is a method by which people investigate and attempt to change and improve conditions for learning. DBR is defined (roughly) as designing in an environment in which to test psychological or educational theoretical constructs. In practice, this often looks like the design of a specific learning environment—which may be a game or a simulation. That environment is typically designed to be an effective learning environment, one where we can verify that people are learning something, but, because the point is to test some theory rather than to design the best system, it still may not be the most effective learning environment.

In DBR, *design* refers to the initial idea, iteration, construction, development, and deployment of some learning environment. Obviously, we are deploying a very expansive version of the word *design*. That said, collapsing all these stages into the word *design* enables us to focus less on the “design research” aspects and more on the education or learning theory aspects. Fundamentally, a design is required to be good enough to enable us to see something with whatever we have created. In some ways, this could be thought of as the design of instruments or tools in a chemistry experiment. For example, if you want to

test the caffeine content of coffee, you need some set of instruments that enables you to see that caffeine content in the coffee solution. Then, when designing your tool, you must keep in mind that your instrument can have some limitations; it doesn't necessarily have to account for every single molecule of caffeine to be useful. Similarly, we need to pay attention to the biases of developers and designers of the tool to identify what the tool tells us about that theoretical construct. For a long time, a lot of DBR did not consider the bias of either the designers or the subjects/participants in an experiment. However, in the past 20 years, exploring these forms of bias within design has, by and large, become required in papers that use DBR.

As so many people have said—not least Marx—it is difficult to see outside of one's default perspective. One word for this (multiply defined over history) is *ideology*: the idea that hegemony exists to “legitimize itself.” To dramatically oversimplify, Adorno and Horkheimer (1997) suggested that the only way outside this self-perpetuating cycle was to understand one's role in the system through intersubjectivity—that is to say, through critical discourse. In this case, that critical discourse must both engage consciousness of the systemic factors (e.g., racism, classism, etc.) along with the context and content of their form. Freire suggests that any critical process in education must always strive toward co-creation of knowledge in the context of those systemic factors and with an eye toward fomenting change. There are a few models of DBR that “bake in” that kind of conscious co-creation; one such model is called “participatory co-design” (PCD; DiSalvo et al., 2017). In our case, we can engage students in critiquing potential designs as we start and have them also generate ideas for designs. Students are typically not trained in design, but they often bring ideas to be integrated into a project through design sessions, and people are typically very quick in PCD to see what “feels false” to them. Does this speak to you (the reader), or does it feel like it targets a stereotype? In our case, we might take a preliminary design to students to play with and have them rip it

apart. The benefit is that the more we do this, the more vocal and specific the co-designers can be (and it might help keep us on schedule, as well).

That said, the design phase is hardly the only place to explore the bias inherent in the system. O'Neil (2016) describes code audits as a very useful tool for examining bias. In an audit, the auditor explores a space of possible inputs and outputs for the software, and looks at them with a critical eye, and evaluates the code itself for implicit bias. For example, if we generate avatars at a specific rate by visual characteristics, why, how, and what went into that decision? Does that decision pander or exclude? Is it editable, is it contextual, is it transparent? Would we be able to support our choices if we were describing it to a diverse audience? Though most audiences do not understand code, they can almost all understand the ways in which the visuals might (or might not) represent the kids who are playing the game. Rather than treating the code as "imperfect and unknowable" (as most projects do, even thoughtful ones), it is incumbent on us to make those implicit decisions manifest.

Bias exists everywhere; even "charitable objectivity" does not exist. We choose which experiments to run, how to build them, when to build them, with whom to build them, when and with whom to test them. The point of design is not to somehow "escape" bias or create the perfect acontextual research tool, but rather to make it clear how the story of the research is shaped both by designers and participants. The power relationship between researchers and participants is similarly both nuanced and important to unpack.

Learning is not the downloading of knowledge into one's head. Therefore, we cannot reasonably say that a tool taught someone something. A person must engage with the tool intersubjectively. No one can force knowledge into someone's head; we can only reward or punish the results of some knowledge. It's hard enough to find evidence of understanding, as we will see in chapter 4 on assessment futures.

Given these questions, how can we see the relationship between aggregation and anonymity?

AnSpec is a powerful tool for understanding when, how, and why design shapes a learner. How many people are we engaging, and in what way? Remembering Freire's (2018) requirement regarding knowledge co-creation, are we assuming that people are engaging with the technology individually or in aggregate? Are we treating the learners as if they are starkly individual or stronger as a group? Are we asking for, prioritizing, and incentivizing critical discourse? Is this done through the design itself, or through an imagined teacher/facilitator?

A lot of the decisions we make in design revolve around what the designers get in return; what are we designing to motivate? It is said that *nothing in life is free*. The tradeoffs exist both diegetically and at the level of the research proposal. Nevertheless, it is a false dichotomy to suggest that affording people not just choice, but also agency—here, both meaningful choices and the resources to make those choices in accordance with their values and needs—comes without some kind of cost. Typically, the designers want, at the very least, some assurance that the game is “getting played” and that people are either paying for it or that a “customer” gets what they expected. For researchers, this is typically a process that involves a human-subjects review board (an institutional review board or IRB) that often focuses on maximizing the information and options that people must have to engage in the project. It used to be the case in schools that parents and teachers could sign a “permission slip” without informing students, but now even younger students are informed, and their permission is often required. In the case of corporations, which are typically bound by few such rules in the US (though they are subject to many more in, say, the EU), they can collect whatever information they want without asking permission from anyone, as long as there is no explicit breach for which they could be sued. Even then, it is typically cheaper for companies to settle such lawsuits with a cash payout and nondisclosure agreement than to miss the opportunity to collect

such valuable data in the first place. Still, such permission forms ask for data from users, and, even in the most well-meaning IRB proposal, the ways that the information is relayed to learners does not necessarily account for what and how they understand their personal data. Indeed, it would be too much to ask any project to teach data literacy before whatever other work they do; if a researcher is testing galvanic skin response, the intervention cannot require six weeks of instruction on the ways that biometric data might be misused.

Therefore, as in earlier chapters, we stress that it is always incumbent on us to collect *only* that information that we need to collect. This is, perhaps, complicated by this chapter's example project goal of supporting learners in understanding their own data. Looking at the problem from the perspective of AnSpec, we can see that there is space for aggregating some meaningful amount of the data generated by the class. There is also no need to explicitly collect all the data that the students see; as counterintuitive as this may be to any designer, we do not need to keep all the valuable data that we use in the activity. Contrarily, simply keeping around the "types" of those data may be more helpful to all parties; it is perhaps the case that a given website can see the student's home address, but we do not want that information on our servers at any point. A flag for "HOME ADDRESS FOUND" is just as informative while reducing the "risk surface" significantly. A focus on anonymity prompts further questions, as we saw in chapter 2: What information goes to the researcher? What information should be transparent to whom? Does it differ in a project about transparency of data? These questions tie tightly to the question of "what counts as data." How can we design a system that gets the data that would enable us to better understand how to help people understand their data while respecting their privacy and agency? What do we keep?

In graduate school, we were taught to KEEP EVERYTHING. KEEP EVERYTHING ALWAYS. This was repeated enough times in enough classes that we suspect everyone has had an experience in which valuable data were lost and experiments or even whole research projects

were abandoned. There is a lot of value in the perspective—that “researchers cannot know exactly what they are looking for, or it would not be research”—but research cannot come at the expense of learners’ agency and privacy. An important example is the case of Henrietta Lacks, who was robbed of any agency, but whose “HeLa cells underpin much of modern medicine; they have been involved in key discoveries in many fields, including cancer, immunology and infectious disease. One of their most recent applications has been in research for vaccines against COVID-19” (Nature, 2020). The ethical debate over the posthumous rights of Henrietta Lacks and those of her descendants remains open, but we center individuals’ agency as the moral imperative in how we interpret research.

Similarly, we may come to points at which it might also be incumbent on us to share our learner-generated data, disclose what we kept, and explain why we did so. This should not be too high a bar for our work. Is it ever OK to keep data that you would not feel comfortable explaining to a subject? Medical research asks this question consistently, but it may be time to import the question into the learning sciences. Some data about perceived identity may do harm to a learner’s understanding of themselves, and the collection of it may simply reflect the systemic bias of the researchers. An example of this would be disclosing the relative success on a math problem to both the learners’ fellow in-class students and the entire dataset. Data may imply to them that their class or school is “good or bad at math” even though an actual statistical analysis would show nothing of the sort . . . but a complete statistics class would be an inappropriate intervention in the middle of our learning activity.

Every Act Is an Intervention

Frameworks do not offer anything useful unless they are in conversation with an existing idea or structure. Like the frame of a

house, a framework is meant to uphold or—in the case of a scholarly intervention—change something. AnSpec, the framework we are offering here, might help you avoid aspects of our work that are otherwise going unnoticed too frequently; this framework helps denaturalize naturalized bias. While this bias is not unique to AnSpec, the position of much of education and the learning sciences is that praxis—in this case, using theory instrumentally—is the best we can do. Similarly, although all practices are subject to critique, Matthew's advisor, Uri Wilensky, would often ask him: "What did you foreground? What did you background? What is erased?" It is our position that, whether you like it or not, you are acting in the world: every act is an intervention, and, therefore, it is imperative to look through a critical lens as you act.

This critical lens does not just look outward; it is also a mirror. As we think about the problems and phenomena with which we seek to intervene, we must approach our research with the recognition that we might not always be the best individuals for the job. What kinds of agency do young people, other members of our educational communities, and the general public demonstrate in the work that we do each day? In answering these questions, we will take a hard look at our own assumptions about the workings of the universe and our location within these systems. These DBR questions, re-posed here, remind us that sometimes the acts that requires our interventions are found within ourselves and not just in the external and noisy world that beckons at the threshold of our sensemaking.

4

Assessment Futures

There's a fascinating filament woven into the fabric of *Star Trek*: throughout many of the various television (TV) shows, films, and spinoff transmedia content, the utopian vision of science-driven exploration and peacekeeping builds on all-too familiar assumptions of academic evaluation.

Briefly, *Star Trek* is perhaps one of the most historically consistent, though flawed, set of perspectives on just futures in US popular television culture. As Jean-Luc Picard, captain of the *USS Starship Enterprise*, suggests, "The acquisition of wealth is no longer the driving force in our lives. We work to better ourselves and the rest of humanity." Popular media has rarely so succinctly or radically stated such a fundamental statement of values: the embrace of betterment, which includes antiracism, learning, and education. Apocryphally, *Star Trek* was the only TV show that Martin Luther King Jr.'s family would watch together, and he famously saved the series by personally urging Uhura actor Nichelle Nichols to stay on the show (NPR, 2011). Despite such a powerful endorsement, the series remains a reflection of its time, and its treatment of "betterment" is often as sexist, racist, and homophobic as the much less thoughtful TV shows that ran alongside it. Considering the flawed but uplifting space that this show

has maintained for more than half a century, the way it treats schooling in myriad episodes is both well-articulated and entirely retrograde.

Watching the 2009 film reboot, we were surprised to encounter the strict representation of Spock's educational regimen on Vulcan, often portrayed as being "past racism." With their ideological commitment to logic above all else, this interpretation is, unfortunately, not only a reification of dominant educational strategies of US schools in 1997, but also a series of assessment-based schooling principles built on a "logic" of antiblackness and a culture of poverty. Clearly, the movie made no connection between punitive "drill and skill" flashcard methods of early educational technology and "illogic," though we have long known that these methods do, effectively, nothing to teach or measure understanding. Indeed, education, as envisioned in the film, still involves racist bullying (against Spock, for being part human).

One thing that is curious about this development within the film, and across portrayals of education in *Star Trek*, is that the offered academic "AI tutor" is curiously unintelligent. Lacking the nuance of irony, humor, or even the basic flexibility to extend or imagine what a character is seeking, these tutors are portrayed as rote, inflexible, and unengaging. In a world with widespread holodecks, and the possibility to create artificial intelligence smarter than humans, the tutor is simply glorified flashcards. Perhaps even more improbably, this treatment of the old as an assessment-driven new is entirely in line with academic approaches to learning in the non-Starfleet-guided world of the present day.

Perhaps the most infamous assessment at the heart of *Star Trek*, the Kobayashi Maru test, is a standardized exam that is meant to reveal an individual's character based on an unwinnable scenario; it is an adaptive assessment rooted in failure. The Kobayashi Maru test is a simulation in which failure is intended to be inevitable, designed to assess a potential Starfleet captain's resilience in the face of catastrophic failure. While Captain Kirk is diegetically famous for being

the only Starfleet student ever to pass the exam, the 2009 film depicts his “win” as done essentially through hacking the system’s coding and bypassing the pedagogical lessons related to encountering failure. The Kobayashi Maru assessment, like the rest of the depictions of educational evaluation in the distant future of *Star Trek* boldly stays rooted in the stale and unimaginative present.

Considering a failure of imagination when it comes to assessment and schooling in the hopeful articulations of white-authored science fiction, this chapter begins with a foundation of how assessment falls across the AnSpec before offering alternative examples to drive research design and practitioner implementation.

What Is Assessment?

Assessment is a term that pretty much everyone in educational research dreads. To a principal, it might mean verifying that classes are teaching some specific content. To a teacher, it might mean a test. To a student, it might mean judgment. To most, the word itself is more of a threat than a specific class of ideas. In the abstract, it simply means evaluative information; people receive evaluative information as *feedback*. What happens with that feedback and how an individual can respond and act upon it, are important outputs of feedback and assessment models, necessary for research design to constantly keep in mind. At the same time, feedback is a mixed term. It may squeal dissonantly on a guitar. It may mean that people think your pants look nice (or not). It may be helpful guidance on what you can do better next time. In almost every model of learning—cognitivism, behaviorism, direct instruction, sociocultural constructivism, apprenticeship, and so on—feedback plays a central role. Indeed, it is almost impossible to imagine a version of improving or augmenting knowledge or processes without some evaluation of current knowledge or processes.

Feedback and assessment are at the center of most traditional models of learning and of processes for growth and development writ large. We learn through feedback measures, and these become systematized and made into routines of schooling, for better or, more often, for worse. Such feedback typically helps evaluate measures of competence and ranking measures. The SAT and ACT are, fundamentally, ranking measures. One's score only has meaning relative to those of other students, and the score is either higher, lower, or the same.

Though the assessments that may come to mind (and are exemplars in parts of this chapter) are the big, high-stakes, anxiety-inducing summative tests that may function as gatekeepers in different parts of a person's individual growth, assessments often function in formative ways. Measuring progress continually and along the way to the culmination of a learning journey is an important component of education design and this chapter's consideration of assessment design, measurement, and adaptivity holds for both summative and formative models.

Further, assessment models are not static. They are often developed to adapt to the needs of test designers, takers, and readers of the results. Although we will consider adaptive assessment as a core premise throughout this chapter, we offer two sets of design questions for teachers, researchers, and policymakers based on adaptive assessment:

- *How* does assessment adapt in your design and implementation? What are the flexible components that undergird adjustment?; and
- *Who* does this adaptivity address? What stakeholder needs are taken up in your adaptivity design and why?

These are not questions that have been pushed imaginatively within schools and educational research contexts. Historically, adaptation is tied to market-driven demands and to outputs related to college and career readiness. Adaptation is often understood as related

deficit views of learners—linguistic, cultural, and age-based framing of “who individuals are”—rather than framing their potential capacities in other ways. Likewise, some form of adaptive assessment is almost always included in the promise of an equitable and transformative future of education. Adaptive assessment is, at its core, the idea that a learner will be evaluated by their practice—that an evaluation of someone’s understanding of a topic will change to fit the person. Yet, when it comes to how assessments are understood in educational policy, in on-the-ground enactment, and in the public consciousness, tests usually are greeted with a mixture of drollery and dread. Assessments can feel boring, punitive, and unfair.

There is little to no qualitative feedback embedded in a numeric test grade out of 100. That fact is central to the logic of quantitative assessment, making it easier to abstract and compare student performance. The driving test, in comparison, is a test of competence: you either pass or fail. Passing is the result of the testers deciding that you are sufficiently skilled at driving; failure means the opposite. There is no concept of ranking; it does not make sense. Similarly, few assessment scholars would argue that someone who has done well on the SAT is skilled at any task or has any particular understanding other than doing well on the SAT.

Assessment and Data

As we explore the role of assessment, we need to ask a fundamental question: How has assessment gone so wrong? Consider most formal measures of assessment and testing that take place in schools and societal governance. From high school exit exams to SATs to Graduate Record Examinations (GREs) to tests for drivers’ licenses to bar exams to practice law in various states, formal assessments mostly fall into very specific genres. Such a limited approach to assessment clearly produces high stakes. Student outcomes and graduation rates

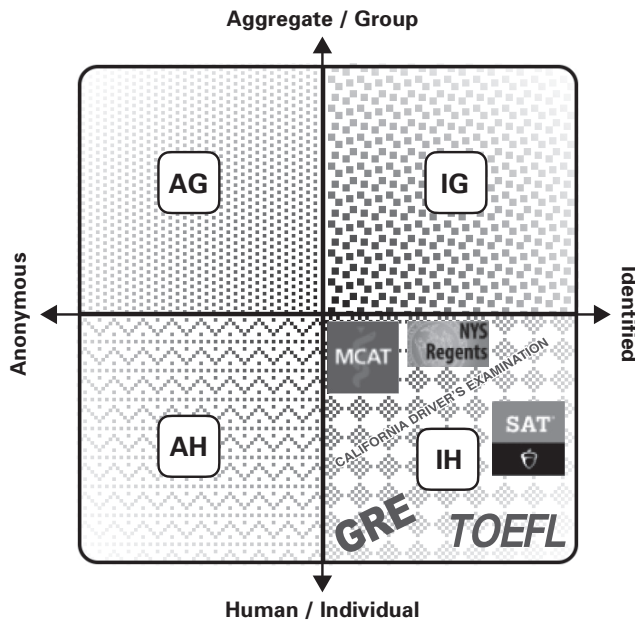


Figure 4.1
Formal assessments plotted on AnSpec.

and teacher evaluation measures in K-12 contexts are both prominent ways that assessments have lasting outcomes beyond measuring a skill set. Further, the cultural legacy of tests shapes outcomes profoundly. That pit in your stomach before a late-night cram session may, depending on your circumstances, reflect a legitimate rationale: stereotype threat, testing bias, and the gatekeeping of the profit-driven “test-prep” industry all speak to the unfair footing that economically-disadvantaged people have when it comes to taking tests.

We want to illustrate how assessments in school contexts typically fall across the AnSpec. This includes typical assessments encountered in schools, Scholastic Aptitude Tests (SATs), exit exams, Advanced Placement (AP) tests, Graduate Record Examinations (GREs), and so on. Plotting these different exams across the AnSpec looks like figure 4.1.

Looking at this figure, the pattern is perhaps all too obvious. All these examples, as well as most assessments that happen throughout K-12 schooling, fall into the Identifiable Human (IH) quadrant of the AnSpec. Though the data from exams might be parsed and examined in different research contexts, from the vantage point of the test taker and of the assessing entity (a teacher, organization, etc.) these tests all function in near-identical ways on the AnSpec: a test is taken by an individual whose identity is recognized by formal measures. At the risk of stating the obvious, there are good reasons for this pattern in schooling assessments. It is easy to locate where a specific individual's progress or proficiency falls across expected measures if we know who that person is as an individual, especially if we can compare that person to groups of similar people. However, there are also good reasons *not* to reinforce this pattern of measuring and gatekeeping within society.

What can we do? Why can we not imagine other possibilities for how assessment is enacted or developed in schools? It's not that educators love the IH-centered approaches to assessment. We posit that this clustering in purpose and design is something largely invisible to how our field designs and enacts assessment.

We recognize that assessment and evaluation are giants of the educational research realm. They are (often) well-funded, rigorous disciplines that guide student and teacher learning experiences. This chapter does not seek to uproot (all of) the practices and research-based knowledge about educational assessment or teacher evaluation. Rather, we hope that the spread of approaches cast across the AnSpec will allow our field to point to and wonder about unexplored possibilities in assessment design. *What would happen if we repositioned student identity? What if our evaluation of student knowledge was adaptive across different dimensions?*

As we move across the AnSpec quadrants to explore adaptive assessment, throughout the rest of this chapter, we offer some guiding

Table 4.1
Adaptive assessment questions for purposeful design

-
- Why do formal schooling approaches to assessment (adaptive or otherwise) cluster in specific quadrants? What does this say about imagination and educational design?
 - How do the clusters of assessment in the past and in your own designs speak to the treatment and categorization of student knowledge and interest?
 - What kinds of agency does an assessment presume within the individuals taking it?
 - How could various kinds of learning spaces move fluidly across AnSpec? What do such spaces require for powerful design?
-

questions about both the past enactments of adaptive assessment and about the role of design, research, and speculation for future-oriented designs (table 4.1).

Playful and unexpected examples of adaptive assessment nestled in everyday life may at first appear like benign diversions from the august world of school-based assessment. We offer playful approaches to assessment to intentionally seek data that is rooted in justice. By (hopefully) upending the perceptions of what counts as an assessment and how such data is developed, collected, and used, we are attempting to extricate assessment from its singular and limited residence in the IH quadrant.

Speculative Assessment, Data, and Justice

Given this chapter’s goal of exploring a wider perspective on adaptive assessment, examples of adaptive assessment can come from software in which it serves a transparent purpose. In playful contexts, many games use some form of adaptive assessment, explicitly or implicitly. Even board games often include complex mechanics to “even the

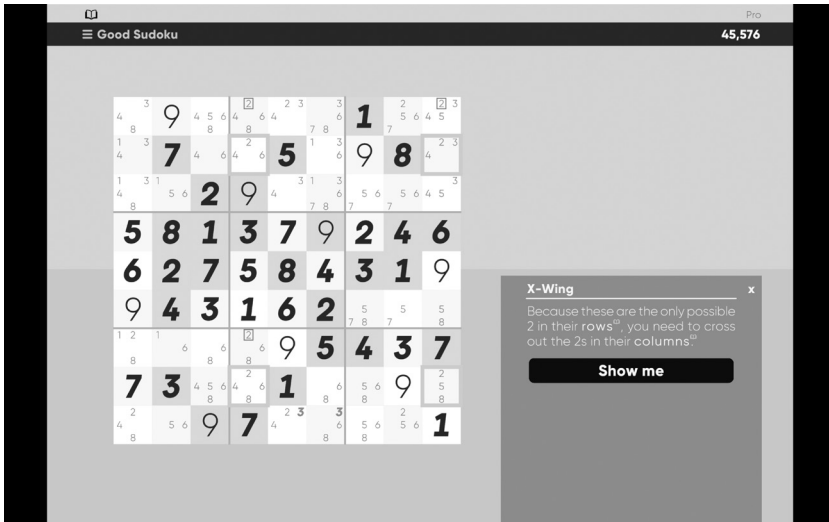


Figure 4.2

Good Sudoku (Gage, 2020) suggesting a possible course of action.

playing field” in ways that require an “assessment” step to evaluate current success.

Anonymous Grouped (AG)

One particularly thoughtful example of a public-facing puzzle game is *Good Sudoku* (Gage, 2020). Sudoku (figure 4.2) is a number game played on a 9×9 grid in which you want to find the single unique solution in which the digits 1–9 are not repeated on a row, a column, or within a “house” (a 3×3 subdivision of the board).

Good Sudoku is frankly a terrific game for several reasons. One of its core features is that it assesses the quality not only of your play (i.e., score) but also of your strategies, using a relatively complex algorithm (described in Eggplant: The Secret Lives of Games, n.d.) that is both clear that it is being used but is designed to feel “unobtrusive” to the player. Over time, the adaptive assessment finds examples of times that you must use a specific named strategy to make a play on

the sudoku board. If you correctly use the strategy a predetermined number of times, you are assessed as being proficient, and a pop-up announcement informs you that your competency has been evaluated. If you make a mistake with that strategy multiple times, it suggests specific training in that strategy. Also, you can ask for hints, and it will explain to you why a given strategy is the correct play for your specific board.

This is AH data: it does not care who you are, other than “someone who would pay to play sudoku,” but it records every relevant play and makes judgments on how best to support your progress. The only negative feedback you might receive is nothing more than a lower score in a game where scores are all but meaningless. That is, if the player eventually solves the board correctly, scores in sudoku are more contingent on the semi-random configuration of the board than the skills of the player. Most of the other sudoku games we’ve played do not even keep a score other than “boards solved per difficulty level.” It may be that the “noninformationality” of the score is what leads to the possibility of more robust feedback in assessments.

The inversion of that statement becomes: “Informational scoring likely leads to less robust assessment feedback.” This refers to situations in which the scoring is plain and the score itself provides the correct answer. For example, if a teacher marks the statement “All elephants have polka dots” as incorrect on a test, the graded student now knows that some or all elephants do not have polka dots. Very little else is needed or given, but there is also no intuition that this information will be used in any contextual way.

Identifiable Grouped (IG)

Matthew has spent several years working on the *Beats Empire* project with scholars, researchers, designers, students, teachers, and schools to create a “just” assessment that lives primarily in the IG space. Beats Empire is designed to be a *culturally relevant assessment game* for New York City (NYC) public schools that provides feedback to

teachers regarding what their *class* understands about the grade-level computer science content. In *Beats Empire*, students manage a music studio and collect and use data to make decisions about signing new artists and recording new songs. There is no single goal: students can choose from a variety of aims, including maximizing money, reputation, and/or fans, or simply making auto-generated music.

The idea is that students play the open-ended game freely just to have fun. Although there are assessment opportunities built into the game, they are entirely unforced. An individual student might play the game across multiple days of class and remain “unassessed” on a given topic. This is very much on purpose: school, by default, assumes individualized (or small-group-level) assessment; there is very little classroom-grouped assessment on which feedback is given to the students and teacher(s). In *Beats Empire*, it is literally impossible to assess a student negatively. There is no way to enforce the “hitting of assessment targets,” so it is much more likely for an individual student to avoid encountering a given assessment opportunity than for that student to fail to understand target content. That said, in each class, a subset of students will almost certainly encounter all assessment opportunities, which provides the teacher information about what the students, in aggregate, do or do not understand.

An open question remains as to how one can judge or support “cultural relevance” in situations in which the students are not identified. In the case of *Beats Empire*, Prof. Betsy DiSalvo (Georgia Tech) led a team of researchers, students, and teachers in co-design sessions in NYC public schools. In addition, we did various levels of fact-finding about both student-content connections and content-theme connections. Though the initial model was not necessarily music-industry-themed, the resulting game leaned heavily both on students’ descriptions of the music industry and the computer science behind analysis in the music industry. The music was one of very few cultural touchstones that every student with whom we talked (out of hundreds in total) had both interest and familiarity; as an industry,

the “moguls” are remarkably diverse and do not fit any easy categorization. In doing data analysis, however, we often found ourselves butting up against the other side of that coin: students would spend a lot of time customizing the game with the music genres they preferred. This worried us: perhaps enough customization would speak to individual student identity? In checking, we did not find any systematicity to who did this and the choices they made; however, this lack of systematicity may speak more to the ways that music is taken up in NYC than to anything else.

The potential upsides to the project seem clear: students enjoy learning and interacting with the target content; teachers get feedback about which content their classroom understands best; there is little opportunity to rank, punish, or judge individual students; there is less of a “privacy surface” for any individual’s data; and the teacher remains the authority on teaching and assessing their classroom. The biggest tradeoffs, then, become clearer: it is a deeply unfamiliar modality of assessment. Indeed, the idea that the assessment exists at the classroom level has been something that many teachers have had difficulty integrating. Historically, if a student has had trouble understanding an idea, a teacher can work with them on it. At the classroom level, do “problems interpreting bar graphs” imply that the syllabus should be amended? What if you, as a teacher, believe that the students know otherwise? What if they have recently done pretty well, in aggregate, on an exam that used bar graphs?

These issues led us, for better or worse, to a teacher-focused dashboard tool rather than a report. Our dashboard (Kumar et al., 2022) supports live classroom management at the level of “Bobby has been idle for 18 minutes”; offers classroom “reports” on what is clearly understood; and provides “insights” with some suggested options for what to do about the reports. For instance, if nobody in the class has used “digital storage” in the game and time is limited, the teacher could suggest the value of using it; conversely, if most students have

used digital storage unsuccessfully, it may be time to have a quick refresher lesson on the relationship between data collection, storage, and access.

Fundamentally, these matters bring up the classic problems of any assessment: What does an assessment tell us? What is being assessed? How well does this assessment map to future tasks or future assessments? These questions are, perhaps, even more difficult to address when the data are not individualized.

Identifiable Human (IH)

In the opening of this chapter, we explored the clustering of multiple school-based assessments as Identifiable Human (IH) data in traditional education. As we saw, many people believe it is preferable or even definitional to education in the US. It is possible to imagine many situations in which you would like the data collected to be individualized and identifiable (that is, IH). *Personalized learning* is a term often used to envision a better future for education, in which each student is taken seriously as an individual. Strengths and weaknesses are evaluated individually and are not bound by the speed or skill of other students, such that a student might be able to progress without public embarrassment or fear of failure. Such a system might provide the opportunity to try out ideas with a personalized tutor in a more pedagogically sound manner. The science fiction series *Ender's Game* posits this sort of personalized world in which each student is individually tutored (and assessed) by an artificial intelligence (AI) and, as a result, individuals would not be held back by the nature of classroom teaching. There is a visceral strength to this vision: many people who try to envision educational futures often come up with models that involve personalized assessment or personalized instruction at some level (often exemplified by a robot such as, say, H.E.R.B.I.E. or H.U.B.E.R.T. in Marvel Comics; see Byrne, 1982). It happens so often in such similar ways in movies, TV shows, comic books, and novels that even a short list of these would drag.

The fundamental problem with these mechanized models is that many of these examples and models incorrectly suggest (or assume) learning to be an individual endeavor, one of the things we know to be false about human learning. Humans, to put it simply, learn better with and around other humans, even in situations in which automated tutors exist.

We did not always assume this about learning and assessment. Indeed, as we saw earlier in the chapter, most current schooling assumes that assessment should happen in isolation, though that model is intrinsically at odds with everything we know to be true of assessment.

Matthew received his Ph.D. from Northwestern University, one of the first “Learning Sciences” programs in the world. It was founded, in part, by Roger Schank, whose concept of the goal-based scenario (or GBS) was originally designed as a replacement for school. (Indeed, Schank repeatedly expressed his desire to “blow up the schools,” though that meant something different—significantly less violent—in the 1980s.) A fundamental conceit of the GBS was that people are all interested in *something*: some set of professions or tasks or experiences. The classic example from the GBS world is a firefighter. The GBS would teach that student all the content they needed to know to become a firefighter, and the assessments would be designed in concert with firefighters. However, because a GBS is computational, the content could be constructed, manipulated, and structured in ways that a learner would come to understand complex content in the context of firefighting. For instance, one would learn calculus because it is necessary to become a phenomenally skilled firefighter—perhaps pertaining to flow rates under heat and pressure. In the GBS, the traditional content of school that was not or could not be useful for a given profession would be ignored, and the assessments could theoretically be tailored to the individual student’s interests, skills, and talents.

In hindsight, Schank and his successors found the problems with GBS to be manifest and manifold: it assumes very difficult—if not

altogether false—things about how we might design for learning and assessment. Without pedagogues judging, assessing, and/or being part of the learning experience, people may learn little and experts trust the results perhaps even less. Furthermore, making an automated learning experience and automated assessment strategy for every possible set of student interests is an unfathomably huge task. There exist tens of thousands of possible contents with different sets of information—maybe you could break this idea down to a few hundred, but this is still a massive undertaking that would take tens of thousands of people many years just to verify, even if the simulations could somehow be generated. Schank, at the time, suggested that the modern institution of secondary schooling takes tens of thousands of people thousands of hours a year, but that we are confident that it teaches people relatively little.

Schank and Abelson's (1977) vision of assessment was that experts could come up with more authentic assessments of the kinds of tasks that they found valuable—but content expertise is not pedagogical content expertise, nor is it assessment expertise. Basically, being a terrific swimmer does not mean you are any good at teaching people how to swim, nor does it mean you are much better at figuring out how good people are at the subtasks that make up swimming (even if you might be very good at assessing if someone is an expert swimmer).

Anonymous Grouped (AG)

Anonymous grouped (AG) cases are simultaneously the most common and the hardest to describe. There exist innumerable situations in each day in which you are assessed both anonymously and in a group. In some sense, every randomized controlled trial, every election, every concert, every crowded event is an AG assessment.

In the US, voting is a canonical AG assessment: people are assigned representatives and referenda are passed based on the ways that people participate and act in groups. It is enshrined in law that these things are inherently anonymous. It is not possible in the US to find out how

an individual has voted. This is for good (probably obvious) reasons: if you were assessed as an identified individual, then the government you did not vote for could arrest you based on your vote. Sporting events feel like natural AG assessments. For instance, often players on a baseball team will do better when the crowd is louder. The crowd can give energy as a group to the players and the players will often assess the value of the crowd: “Their hearts weren’t in it tonight!” Similarly, concerts have a language for their assessments: “I can’t hear you, Toronto!” As with everything in this book, all these examples exist on a spectrum. A concert is purely anonymous and aggregated; it is impossible for a performer to tell if you, specifically, sang along, but easy to tell if “people are singing along.” Basically, the more the data can be aggregated, the more inherently anonymous they are, and the less chance there is for any possibility of identification.

The question remains: Are these examples, strictly, assessments? They are assessments in the sense that performance and action result in judgment, consequences, and feedback. They are not assessments in the sense that it is often hard, due to the level of aggregation, for a participant to evaluate their own participation from that feedback or judgment. That is not to say that AG assessments are meaningless, but rather that their meaning exists at a different grain size. Baseball teams make radical changes if people stop showing up to games or start cheering more quietly. Concerts will avoid “dead” towns. Bad politicians will be elected. These results all stem from AG assessments, and the implications—while at an aggregated level—affect all the individuals who participate in them.

Toward Just Futures: Radical Visions of Cross-Spectrum Assessment

This chapter began with the dreary reminder that assessments are rigidly mired in tired molds. In popular culture, in public imagination,

and in the lived experiences of young people today, all assessments seem born of the same mundane model that houses implicit bias and undue stress for test takers. When we look beyond schooling contexts, this simply doesn't have to be the case. When we imagine assessments that are more than the summative task of identifying a particular individual and declaring how that person measures up in the world, the possibilities of assessment—and the outcomes of it—become potentially transformative.

As designers of assessments, what might it mean to push our vision of design beyond singular and identifiable individuals? Like the previous chapters in this section, we think there is a necessary task in our field of playing across the AnSpec, dabbling in assessments that honor anonymity and imagining how such models might transform individual learning experiences.

Even in the future, the most radical visions of assessment that lurk in the flashback scenes of popular science fiction reveal digital flashcards and individual-assisted tutoring systems. We *already* have these models in the present day, and they thrive alongside generations of educational inequality. Missing in many of these models is the treatment of data: where do the results from assessments *go* when students take the SAT today or when Captain Kirk aces the Kobayashi Maru test in *Star Trek*? From our vantage point, there seems to be an impoverished view of how learners' data might be used ethically in the present and future visions of assessment and data science.

As we wrap up this chapter, let's go back to *Star Trek* for a moment. Remember all those restrictive assessments and the regimented forms of tutoring systems and tests designed for failure? Fortunately, that's only one dimension of the projection of learning and evaluation in the future. From our vantage point, the storytellers in *Star Trek* seem committed to data privacy in surprisingly deep ways. Though networked computers very much existed at the time, private data generated by individuals—and even the tracking location of those individuals—was encoded physically onto disconnected tablet devices called

PADDs (sometimes credited as an inspiration for the Apple iPad). In one scene in *The Next Generation* series, Counselor Troi is moving out of her office, and she finds that she cannot cram enough PADDs into her suitcase. In other words, you cannot even move data between PADDs, and, if you lose them, those data are lost. In every series of *Star Trek*, as far as we can tell, anyone living in the United Federation of Planets (the “good guys” for whom the *Enterprise* is an exploration ship) can put effectively unbreakable encryption onto their private/personal data if they so wish.

The vision of data privacy hinted at in the PADD design is an important consideration for assessment designs and helps reframe a consideration of whose data is anonymous for whom. The AnSpec is not a tool for simply rigid plotting of different assessment batteries. Rather, we want this heuristic to help flex and push on the boundaries of what is possible in classrooms transformed from the here-and-now. Fundamentally, any vision of “adaptive” education involves personal data: how else would it “know” you well enough to get better if you don’t know what understandings you lack? Just as *Star Trek* cannot depict a world in which those data are used both fairly and privately, we see the tensions underlying identifiable and anonymous, between range and scale, and between grouped and individualized data at odds in assessment development. As we seek assessments that live *across* the AnSpec, this chapter illustrates possible pathways across spaces unfamiliar to traditional modes of schooling.

Interlude: Assessment

Part of our skepticism about mechanized models of assessment is a basic, yet overlooked, fact: simple code can reinforce existing systemic inequities. Here we offer actual, runnable Python code (targeted at programming novices) that implements an adaptive assessment for a grade-school mathematics student. The way to wade through this code—regardless of your programming proficiency—is to notice how basic, core decisions (that a programmer might not even consider!) will generate inequitable outcomes for students. Assessment inequity does not require malevolence; we’d hazard that almost everyone in the field of education means well. Though building an adaptive assessment may sound complicated, it does not have to be. It is our hope that even nonprogrammers will be able to read the following program code and see points at which good intentions generate problematic situations.

Matthew teaches a class on computational research in education: an adaptive assessment like the ones here can be built by a relatively novice student for a week’s homework. Like everything in the book, building an assessment in which bias is exposed and which leverages or at least considers notions of equity in the structure of the assessment is not necessarily harder. Let’s say you start with a simple math problem. In Canvas (a system used in classes at both Stanford

and UW–Madison), instructors with no programming background can create a problem generator. The following text offers such a tool in Python for a basic arithmetic class (if this sample looks intimidating, the language that follows “#” is a step-by-step guide explaining what each line does and how).

```
# we will use randomness in this code, so we need to “import”
# what’s called a “library” - you can look up any number of these
# at python.org - there are hundreds.
```

Comments start with a #. Anything on the line after a “#” is not run by the computer. It is only for humans reading the code.

```
import random
```

```
# def declares a function in python
# a function is something that can be called repeatedly
# calling addend() returns an integer between 0 and 9
```

A *function* can be run repeatedly. Typically, just as in mathematics (e.g., $f(x) = 2x$), a function takes *parameters* and *returns a value* (in this example, x is the parameter in $f(x) = 2x$ and, say, 6 would be “returned” when x is 3).

```
def simple_addend():
    # random.choice() takes a list and returns a random element
    # range(N) returns a list of integers from 0 to N
    return random.choice(range(10))
x = simple_addend() # random integer, eg 5
y = simple_addend() # random integer, eg 7
```

```
# int() takes a string (text) or number (such as 3.442)
# and tries to give you the integer of that
# for example, int(2.332) == 2
# input(“hello!”) prints that text (here: hello!)
# and then waits for user input
# int(input(text)) turns the user input into
# its best guess of an integer
```

Python has built-in functions—such as `int()`, which we describe to the left. You can also write your own—such as “`simple_addend()`” just above.

```

response = int(input('\n{ } + { } = ?\n'.format(x,y)))
if response == (x+y):
    print("correct")
else:
    print("incorrect")

```

```

>>> 4 + 7 =?
user> 11
>>> correct
>>> 9 + 8 =?
user> 17
>>> correct

```

This is what it looks like when you “run” the code above. The running of the code generates the language signified by `>>>`; user input is denoted *user>*; and Python’s responses are denoted `>>>`. You can run this code at the links included with this book or at the website (nothing is required other than a browser; nothing is installed).

If we add a “difficulty” parameter, we can make the math problems randomly harder or easier.

```

# this time, addend() takes a parameter, difficulty
def addend(difficulty):
    # we never want difficulty below 1,
    # so we always take the maximum of
    # the two options: difficulty and 1
    difficulty = max(1,difficulty)

    # we multiply difficulty by our random
    # integer, likely making it
    # a more difficult number to add
    return difficulty * random.choice(range(10))

```

Here we are defining a function we have named *addend* which takes a *parameter* that we have decided to call *difficulty*. When it is called, it generates a random number that is simply the parameter *difficulty* times a random number that is either 0, 1, 2, 3, 4, 5, 6, 7, 8, or 9. (The first line of code after the comment just limits the difficulty to 1 or larger.)

```
# difficulty starts at 3
# since our range above is 0–9, addends now
# range from 0–27
difficulty = 3
x = addend(difficulty)
y = addend(difficulty)
```

We then generate two random numbers with *addend* (which are different every time the program is run) and that we have creatively and memorably named *x* and *y*.

```
response = int(input('\n{ } + { } = ?\n'.format(x,y)))

if response == (x+y):
    # if correct, we make things harder for next time by
    # adding one to the difficulty
    difficulty += 1
    print("correct")
else:
    # if incorrect, we make things easier for next time by
    # subtracting one from the difficulty
    difficulty -= 1
    print("incorrect")
print("difficulty is now {}".format(difficulty))
```

We take *input* from the user, and we respond by acknowledging the response and updating the difficulty.

```
>>> 12 + 3 = ?
user> 22
>>> incorrect
>>> difficulty is now 2.
>>> 21 + 6 = ?
user> 32
>>> incorrect
>>> difficulty is now 2.
```

This is what it looks like when it is run. Again, `>>>` is what Python produces, and `user>` is what the user types.

That process is not particularly tricky. The process becomes something only slightly trickier when the problem generated has to be adaptive.

In some sense, we can call it a day. We have created an adaptive assessment. The more problems that a student gets right, the harder the following problems become, and the teacher gets a “max

difficulty” score. Not only that, but because the tool doesn’t penalize you for getting a question wrong (instead making the next question is relatively easier), you are incentivized to keep going without having to worry about working on problems that may be a bit too hard. Sounds good, right? So, what is wrong with this?

The biggest sticking point is that very few problems scale in the way this generator is designed. The problems that do scale rarely assess understanding meaningfully. For that we need “features.”

As we saw in many of the cases in this chapter, the decision of what counts as a *feature* (e.g., a measurable aspect, an axis, a column, a dimension) is extremely fraught. As we will see through the following code examples, “feature engineering” is a salient way that bias and control are baked into the algorithms that shape modern schooling. Despite the cutting edge-allure of AI, the cleaning and quantizing of data is a job that is tedious, tiresome, and relegated to the status of rote labor. Much of the feature engineering on massively successful machine learning in the marketplace is done by novices and interns.

Going back to our example again, we create something simple but include two features:

```
def addend(difficulty_range):
    # random.choice() takes a list and returns a random element
    # range(N) returns a list of integers from 0 to N
    return difficulty_range * random.choice(range(10))
```

The *addend* function is the same, but now instead of varying the difficulty only through the number, we are adding a new function we have called *arithmetic_operation* that also takes the *difficulty* parameter. We are proposing that subtraction is inherently more difficult than addition and that we can generate a tricky two-feature problem with this same *difficulty* parameter.

```

# this function returns a function (like in math)
def arithmetic_operation(difficulty):
    if difficulty < 3:
        # at low difficulty, addition
        return ("+", lambda x,y: x+y)
    if difficulty < 5:
        # at higher difficulty, subtraction
        return ("-", lambda x,y: x-y)
    else:
        # highest difficulty is multiplication
        return ("*", lambda x,y: x*y)

def two_feature_problem(difficulty):
    x = addend(difficulty)
    y = addend(difficulty)

    # calling arithmetic_operation() returns the name
    # so we can print it out to the user
    # and the function, so we can do the calculation
    # ourselves to check their answer
    op_name, op_function = arithmetic_operation(difficulty)
    response = int(input('{} {} {} =?'.format(x, op_name, y)))
    if response == op_function(x,y):
        difficulty += 1
        print("correct")
    else:
        difficulty -= 1
        print("incorrect")
    print("difficulty is now {}".format(difficulty))

# we have changed the difficulty
# so we need to tell the program
# outside the function the new difficulty
return difficulty

```

```
difficulty = 4
```

```
# do this 3 times
for i in range(3):
    # since this changes every time, we set it equal
    # to the returned value of the
    # two_feature_problem function
    print() # separate the lines
    difficulty = two_feature_problem(difficulty)
```

```
>>> 0 - 28 =?
user> -28
>>> correct
>>> difficulty is now 5.
>>> 25 * 30 =?
user> 3
>>> incorrect
>>> difficulty is now 4.
>>> 36 - 24 =?
user> 12
>>> correct
>>> difficulty is now 5.
>>> 12 - 4 =?
user> 3
>>> incorrect
>>> difficulty is now 3.
>>> 15 - 9 =?
user> 3
>>> incorrect
>>> difficulty is now 2.
>>> 12 + 8 =?
user> 0
>>> incorrect
>>> difficulty is now 1.
```

We can see here that the problems become meaningfully more difficult as you succeed at them and easier when you fail. For the example, we input that $25 * 30$ is 3, but we have calculators and know that it is secretly an entirely different number. Sadly, that number, like so many, is unknowable and/or 750.

These features introduce a new, more fundamental question: Should operation and range scale difficulty in the same way? This short code segment masks the equity implications of the scaling: different students will excel at different trajectories through these problems. For some students, addition of negative numbers will halt their progress; others might stop at the multiplication of multidigit numbers. It may be that there is a systematicity to these different trajectories. Considering the ways these would play out in the real world, it is incumbent on programmers to account for different trajectories.

Teachers use tools every day that carry inherent assumptions or biases, and, because these assumptions might be buried within the implicit logic of simple code (e.g., like the preceding code), they go unexamined. It's not even clear that anyone involved with many of the systems would be aware of the need to look for systematic problems of this sort. Raising awareness that even simple code like this contains inherent systematic inequity (often residing in the IH quadrant of AnSpec) is not enough. One possible best practice would be to agree that adaptive software offers some way to expose assumptions. Although it does not “fix” the inequality baked into an assessment, it at least makes such inequality obvious. Unfortunately, this either requires the user (in this case, teachers who already have plenty of other demands on their schedules) to dedicate their time to learning how to do critical analysis of code, or requires us to create some sort of language for exposing and expressing these biases in ways that do not require teachers get another master's degree. Turning the preceding code into an assessment only requires keeping track of the assessment implicit in the adaptivity:

```
def analyze_incorrect(user_answer, x1, x2, op_function):
    possible_operations = [lambda x,y: x+y,
                          lambda x,y: x-y,
                          lambda x,y: x*y]
    correct_answer = op_function(x1,x2)
```

```

# if they simply flipped the order or used another operation
# lower the difficulty of the operation
if user_answer in map(lambda op: op(x1,x2), possible_operations) or
user_answer in map(lambda op: op(x2,x1), possible_operations):
    print("are you sure you did the right operation?")
    return (0,-1)
# don't change range, make operation less difficult
# or if they were within 10% of the correct answer
# then change the range, but don't change the operation
elif abs(user_answer - correct_answer) <= abs(0.1 * correct_answer):
    print("are you sure you did the calculation correctly?")
    return (-1,0)
# otherwise, no guesses! difficulty for both is lowered by one
else:
    return (-1,-1)

difficulty_range = 3
difficulty_operation = 3
max_range_difficulty = 0
max_operation_difficulty = 0

for i in range(5):
    x = addend(difficulty_range)
    y = addend(difficulty_range)
    op_name,op_function = arithmetic_operation(difficulty_operation)
    response = int(input('\n{ } { } =?\n'.format(x,op_name,y)))
    if response == op_function(x,y):
        difficulty_range += 1
        difficulty_operation += 1
        print("correct")
    else:
        delta_difficulty_range, delta_difficulty_operation =
        analyze_incorrect(response,x,y,op_function)
        difficulty_range += delta_difficulty_range
        difficulty_operation -= delta_difficulty_operation
        print("incorrect")
print("range difficulty is now {}".format(difficulty_range))
print("operation difficulty is now {}".format(difficulty_operation))

```

```

max_range_difficulty = max(max_range_difficulty,difficulty_range)
max_operation_difficulty = max(max_operation_difficulty,difficulty_operation)
print("user score (max range difficulty): {}".format(max_range_difficulty))
print("user score (max operation difficulty): {}".format(max_operation_difficulty))

# ** a sample run **
>>> 24 - 3 =?
user> 21
>>> correct
>>> range difficulty is now 4.
>>> operation difficulty is now 4.
>>> 32 - 20 =?
user> 12
>>> correct
>>> range difficulty is now 5.
>>> operation difficulty is now 5.
>>> 25 * 35 =?
user> 875
>>> correct
>>> range difficulty is now 6.
>>> operation difficulty is now 6.
>>> 0 * 48 =?
user> 0
>>> correct
>>> range difficulty is now 7.
>>> operation difficulty is now 7.
>>> 21 * 21 =?
user> 2
>>> incorrect
>>> range difficulty is now 6.
>>> operation difficulty is now 8.
>>> user score (max range difficulty): 7
>>> user score (max operation difficulty): 8
>>> 21 - 3 =?
user> 0
>>> incorrect

```

```

>>> range difficulty is now 2.
>>> operation difficulty is now 4.
>>> 12 - 16 =?
user> 0
>>> incorrect
>>> range difficulty is now 1.
>>> operation difficulty is now 5.
>>> 9 * 1 =?
user> 0
>>> incorrect
>>> range difficulty is now 0.
>>> operation difficulty is now 6.
>>> 0 * 0 =?
user> 0
>>> correct
>>> range difficulty is now 1.
>>> operation difficulty is now 7.
>>> 3 * 9 =?
user> 0
>>> incorrect
>>> range difficulty is now 0.
>>> operation difficulty is now 8.
>>> user score (max range difficulty): 2
>>> user score (max operation difficulty): 8

```

We can see how quickly our adaptive math tutor elides into a sort of de facto (if not de jure) assessment. On the one hand, this assessment is in many ways superior to a classic math test: it does not punish failure, it allows exploration, it is impossible to cheat the system (as the numbers are randomized), and it does not report your trajectory, so to speak. On the other hand, it may make implicit what is understood to be explicit about a test: that it is an evaluation, that it is not expected to relate to lived practice, that it is an exercise for assessment rather than learning. Unless that distinction between the two is

understood by all parties, it is simply another potential opportunity to rank students unnecessarily. There is no expectation that, simply because it is adaptive, it is authentic to any meaningful tasks. That is a dangerous leap, but one that many people seem to make. We may just be reproducing many of the worst elements of school, faster. And yet, here we are splashing in the possibilities of Python. Perhaps we might produce new school elements, generate new pathways for learning, support, and assessment. What might you tweak in your work with code and with the contexts of your scholarship?

5

Schools and Formal Learning Organizations

As much as educational experts might espouse the need for divergent thinking and creativity, a quick skim of popular science fiction and fantasy reveals how fixed our notions of schools and classrooms remain. With only a few exceptions that resist Western notions of schooling models (Okorafor's *Akata Witch* is a particularly useful young adult example), the majority of classrooms and teaching models in alternative worlds or in far-flung galaxies look remarkably like what twentieth-century classrooms look like. These models—derived from medieval Western notions of how universities and formal schools might operate—are relatively new when looking at the timescales of human development and progress. Our relationships with land, with preprint forms of oral literacy, and with guild-like models of apprenticeship have been fundamental forms of schooling eons before “schools” and degrees and Carnegie units ever came into existence. In the same way that we might think expansively about where and how individuals are clustered when it comes to data collection, how we orient student bodies, learning, and instruction has largely been cordoned off to familiar repertoires. Watch children frolicking at a nearby playground, and you’ll see organic forms of teaching and

learning that elide schooling structures that will be encountered later in those children's lives.

As our reflection on *Star Trek* and assessment illuminated in the previous chapter, despite our imaginative descriptions of advanced technologies, magical flora and fauna, and alternate ways of living with more-than-human life, our relationship to learning remains grounded in the terrestrial notions of drill-and-kill high-stakes assessment. And while we might love the idea of moving beyond the unimaginative land of formal learning organizations, we are also all too familiar with the fact that these are the pragmatic spaces to which our work as researchers must attend. With this in mind, we ask you to imagine this chapter's emphasis on deliberate approaches to schooling and data in contrast with the world of schooling *as it could be*. Like a frenzied puppy seeking the stuffing-filled innards of a chew toy, excavate the principles of schooling here and connect with their squeaking, regimented heart. In this way, this chapter offers our first "deep dive" into a context: appropriately, that of schools and other formal learning organizations. We use AnSpec to look at how identity is used as both a tool and a weapon and how AnSpec can help us see where we can improve schools without selling our children's data or dehumanizing them. We also give examples from prospective futures—science fiction in particular—to understand and explore possibilities of schools as a space for resistance.

What Are Schools?

Let us start with the basic premise of this book again: freedom and justice are the ultimate goals of critical use of data in educational research. Recognizing this, we need a clear-eyed understanding of exactly what we are dealing with in schools. From individual student learning metrics to data driving large-scale decision-making, the ways information flows through and shapes schooling contexts is

pervasive and never neutral. What are the creative possibilities made available to students and their teachers daily? How does data shape and stifle? Because this chapter focuses on how data is used and *could be* used in formal schooling settings, we start with a substantive dive into the purpose of schools in the US today. Reviewing the vocational, civic, and social purposes of schools and what they do on a day-to-day basis allows us to understand where data lives and what it does.

Because most of the readers of this book have spent substantial portions of their lives in some form of school at some point, our imagination of what schools look like and feel like may be a bit constrained and inflexible. Sure, the names of classes, the schedules, and the instructional approaches may get the occasional facelift, but as an 8:00-3:00(ish) daily operation that separates students by age and moves them from room to room, a Western model of schooling can feel rigid. We share this to highlight that perhaps the most limiting aspect for how we might imagine (and continually *reimagine*) schools is the fact that we have a collective, shared vision of what schools feel like, what they are supposed to do, and how they are supposed to generally operate on a day-by-day, hour-by-hour basis. Despite this, we know that schools are neither limited to such narrow aims, nor are they shaped in only this way. In fact, some of the things we take for granted about schools and their operation might be insidiously harmful (even if/when they are invisible). For example, most people reading this book (at least in US contexts) might assume that schools *should* be built around several existing criteria:

- a “Carnegie” system of grading (e.g., units and A-F grading);
- students engaging in separate and distinct disciplinary subjects; and
- placing students with peers who are around the same age.

This list reflects the tacit ways in which most people would probably describe what schools do. They are the “grammar” of schooling

as described by Tyack and Cuban (1995). Yet, none of these elements of schooling are tied concretely to student success, much less broadening equitable college and career outcomes for all students or furthering a freer vision of democracy in this country. Rather, these are the systems that our society adopted and adapted while moving toward industrialization more than a hundred years ago.

In our push for a more thoughtful and playful understanding of what justice-driven visions of schooling and data-use within schools could be, we point to these apparent immutable laws of public schooling as the general boundaries of societal imagination. We acknowledge that it is hard to imagine schools today that do not align with these components, yet that is precisely what a speculative approach to justice enables. To understand what we *could* be as participants in educational systems, we want to ground the first part of this chapter in a basic question: “What are schools actually for?”

Perhaps most cynically, schools are a relatively safe place to keep children occupied during the typical workday. The COVID-19 pandemic’s widespread impact in 2020 and 2021 made most explicit to harried parents across the US just how valuable schools are as spaces for “containing” and caring for students daily. This perspective of schools as sites of ongoing infant to near-adult daycare is not usually addressed in educational research, but we name it here to specifically illuminate at least one basic way in which schools function societally. There are historical precedents for this as well. An increase in humane child labor laws in the early 1900s meant that adults needed to seek places to keep children during “regular” working hours. These larger shifts in industrialization moved in parallel to the adaptation of schools from one-room schoolhouses to comprehensive school systems within burgeoning cities nationwide.

This shift illustrates how labor and US citizens’ relationship to it have been the guiding forces for how schools are designed and operated since their inception. To follow this trend, alongside relieving working-class adults of childcare needs, schools have been imbued

with the expectation of preparing young people for the labor market. The idea of “vocation as an aspect of how schools function as part of a larger sociopolitical system” has wide-reaching implications for data collection and analysis, as we explore later in this chapter. One of the schools that Antero taught in as a high-school English teacher was Manual Arts High School, one of the oldest high schools in Los Angeles. We draw particular attention to the name of the school; the “manual arts” of the school name were specifically tied to the labor and factory work that was eventually taken up by predominantly Black and (later) Latinx communities living in South Central Los Angeles throughout the twentieth century and beyond. At sporting events, the school’s mascot, Tommy the Toiler, would wield a large fake sledgehammer, reinforcing the message that this is a school for hard-working (e.g., “toiling”) laborers.

From vocational work and skilled labor preparation to a decades-long emphasis on “college and career readiness” (Pimentel, 2013), the language that describes the necessity of vocational training in this country changes even when the purpose remains the same. We do not mean to say that labor and preparing for it are bad! We recognize several substantial and important ways that these skills are fundamental aspects of learning and society (Rose, 2005). It is not, however, the *only* purpose of schooling.

Just as a US economy depends on skilled workers to thrive, so too does its democracy depend on enthusiastic and competent civic actors. In this sense, another key purpose of schooling is to guide students into civic participation in the social world that beckons to them from beyond the walls of the classroom. From understanding the existing mechanisms of government and politics, to learning to advocate, to understanding how to organize for social good, one role of schools is to instill in students “participatory readiness” (Allen, 2016). Ironically, this purpose has become an almost subversive antidote to consistent measurement, as “citizenship” is itself inconsistent (and, therefore, hard to gauge consistently; Mirra & Garcia, 2020).

Just as the language of vocational training updates from one generation to the next, the emphasis of what civic learning looks like in schools also shifts. Best practices today emphasize curricula that are variously *authentic* and *relevant*. This language signals connections to culture and to the world beyond classrooms and offers important links to the racial and socioeconomic backgrounds of students. This language is also remarkably like language from more than a century ago. Dewey (1899) describes a democratic approach to schooling that sounds remarkably like calls for “twenty-first-century learning” today. The US has been on a perpetual quest to ensure that schools are relevant and mirror the needs and interests of engaging in contemporary society. Ask most students, teachers, administrators, parents, and policymakers and you would be hard pressed to find someone who does not voice a commitment to making schools relevant and meaningful bastions for engagement in the world beyond the classroom. This is a wholly valid and important push for schooling. However, it is a quest that schools have systematically failed at achieving for more than a century.

Today, this infatuation with relevance is called “twenty-first-century learning.” In work with Mirra (Mirra & Garcia, 2020), Antero engaged in a systematic exploration of what twenty-first-century learning actually means or looks like in US research contexts. The results of this work were damning. When we talk about “twenty-first-century learning” in educational research, we frankly don’t know what we are talking about or have a unified vision of what this means. It is from this murky demand for *something* that a wellspring of data-informed disruptions, innovations, and additions to student learning spouts today. In a perpetual quest to fix schools, we have sought creative, relevant, and authentic solutions generated by technology and data-driven platforms (rather than, say, participants). In looking at how this has happened and what it does to schools, we frame the later part of this chapter around what it might mean to

reverse this trend and invest financially, emotionally, and intellectually in the possibilities of young people.

Data and Schooling

Schooling data proliferates. Throughout the different models of schooling described earlier in this chapter, data sorts and guides students and their learning experiences. In myriad ways, students are academically and physically guided toward specific outcomes. Data is at the heart of these decisions, but where that data comes from, what its predetermined purposes are, and toward what overarching ends it is aimed are often occluded from students, parents, and teachers. For example, data has interesting interactions with the notion of schools as preparation for and support of labor. Effectively, the entire research base in education, vocational/business studies, and the learning sciences suggests that students will be best prepared for authentic labor if they are authentically engaged in related material. It is clear that very little of a typical high school student's day engages in authentic labor or production. Indeed, very little of the data that schools generate is about supporting any of their arguable goals, and almost none (if any) of the data they generate is useful to them or even corporations (other than those corporations that want to exploit the structure of school itself, such as textbook and curriculum companies, for example). This is curious, though, as almost all stakeholders—students, parents, teachers, administrators, policymakers, politicians, corporations—would almost certainly value a stream of data about students engaging in authentic tasks. The reasons are clear: consistency and identifiability. Schools have come to value consistency and identifiability of data over the value of the data itself. Though it is clear to everyone involved (especially teachers) that students learn much less when quizzed multiple times a week, many students are

still quizzed multiple times a week in multiple classes as a way for the structures of schooling (and school funding) to regularize, validate, and internally reconcile their Identifiable Individualized (IH) data.

The number of data streams in schools has only grown in recent years. They are a confluence of flowing information about students, about teachers, and about the metrics that various corporate institutions seek that flows *away* from individuals and into the shallows of businesses. Though data has always informed schooling decisions (and kids have been taking quizzes in classes on a daily basis—to the chagrin of nearly all involved—for generations), the sheer amount of data amassed about students today has led some to refer to this process as the “datafication of education” (Jarke & Breiter, 2019; Williamson, 2019). Test scores are one obvious form of data that are likely understood and assumed by most readers. Though parents and teachers may see test scores at individual and identifiable scales, they serve fundamental sorting and budgetary roles at higher scales. Infamously, the 1983 report, *A Nation at Risk*, opened with the foreboding words, “If an unfriendly foreign power had attempted to impose on America the mediocre educational performance that exists today, we might well have viewed it as an act of war. As it stands, we have allowed this to happen to ourselves” (National Commission on Excellence in Education, 1983). This sentiment and the fear-mongering that followed led to ongoing emphasis on test scores and evaluation.

No Child Left Behind, Race to the Top, Every Student Succeeds . . . the names of the various federal initiatives in the 2000s speak to the collective insecurities the USA has placed upon schools about its status and intelligence as a global nation. Our interpretation of data—of the ways we mold and shape young human beings in schools today—is reflected through a lens of capitalist competition. The ethical question underlying these policies has been overlooked for far too long: Is capitalism—and the individual deficit perspectives that it typically reinforces—incompatible with what we want out of schools?

The kinds of demographic information that clues people into the socioeconomic contexts under which a given school operates may also be understood as the kind of data collected. These are forms of data collection that have been going on for decades in the US context, from attendance-tracking systems to online learning management systems that check students' time "engaged" in each set of learning tasks, to eye-tracking software. Currently, these practices are not even necessarily tied to formal academics. From swiping into school facilities to logging on to school-issued devices, the digital footprint left by each student allows schooling systems to track their moment-to-moment lives in myriad contexts.

The prevalence of social media in the lives of students, parents, and teachers today means that even data not intended for the gaze of school officials becomes a part of how schools operate. From online pressure around politicized curriculum like critical race theory to issues of student bullying and privacy, the data streams from content platforms extend far beyond what is assumed to be the traditional boundaries of schools. There are *good* learning opportunities around these differences. For example, educators are considering the porous boundary between the private and closed-off spaces of classrooms and the public nature of writing to an authentic audience (e.g., Lo et al., 2023). These opportunities for engaging in authentic learning extend to models of project-based learning and dated visions of democratic schooling (Dewey, 1903); the promise of social media for engagement is nothing new. Yet, these online tools, too, cause more concern and handwringing than educational innovation. The flows of data were never structured for democratic schooling (Apple, 2004, 2012, 2017).

In early 2021, the Supreme Court ruled in the case of *Mahanoy Area School District v. B.L.* that the school district could not punish young people based on their messaging in out-of-school contexts. Based on a viral message from a teenager shared online, the case was

often shared as a victory on behalf of free speech. However, pertinent to the relationships between schools and data discussed in this chapter, the language of the court does not ring with the promise of freedom. Rather, the ambiguous wording of the ruling allowed schools to potentially regulate forms of off-campus speech in the future, and the ruling generally ignored the modes of data collection and surveillance that have multiplied in today's digitally mediated landscape. Despite allowing this student's words to move beyond the punitive control of a district, this is an instance that feels like a harbinger of how school control and the uses of data will likely move further into most aspects of students' lives.

It is hard to keep track of the myriad kinds of data that flow in, around, and about the lives of young people. Assessing learning metrics, managing behavior, guiding funding decisions, driving policy, standardizing learning expectations, driving social interactions, curtailing physical and digital access to materials, and surveilling young people's actions and bodies: these are basic forms of what data does multiple times every day of students' lives. Bad data and bad interpretations of limited data can lead to historic inequities. The past is a clear indictment. From the Moynihan Report (1965) that blamed Black communities for educational deficits to legacies of scholarship that still today seek to tie measures of intelligence to racial and genetic traits, data are a cudgel for inflicting generational harm on vulnerable communities. Further, how those in power choose to act upon limited kinds of data can only exacerbate the negative impacts of school data. As a 60-year quagmire that continues to rumble forward, for instance, the effects of school desegregation through mandated busing efforts reshaped who made up the teaching profession after *Brown vs. Board of Education*, added thousands of hours of commuting time to the lives of US youth, and remapped where and how schooling transpired in nearly every state (Garcia, 2023). These were data-informed decisions, and their effects continue today, despite the lack

of clear indicators that busing has ever been a “correct” solution to the data of segregation.

We do not write this seeking to abolish data or the mechanisms of capturing it. But we do think we should abolish *bad* uses of data and push scholarly imagination of what data is for and how it is constructed. At the heart of this push, we need to challenge the assumptions of what data is for and how it conceives of young people as a problem.

Constructing and selling youth identities Looking at the prevalence of learning management systems and digital learning platforms in school contexts today, it is clear how these systems function as the infrastructure on which schools operate. Day-to-day decisions about the needs of schools are operationalized by the data collected about students. These data, then, are not measures of many of the components of schooling that were noted at the beginning of this chapter. A student’s inquisitiveness, sense of safety and well-being, joy, or civic development are rarely meaningfully measured.

Further, although the plethora of data here is collected at the individual level, it is interpreted *en masse*. In this way, we use AnSpec to look at how identity is used as both a tool and a weapon and explain how AnSpec can help us see where to improve schools without selling our children’s data or dehumanizing them. Whereas the language of schooling professional development might focus on individual learning plans and customization for student needs, data is typically collated into a valent trend of Identifiable Grouped (IG) and Anonymous Grouped (AG) data to inform decisions. Schools often create aggregations such as “English language learners” and “special education students” to evaluate the variance in data generated by individual students; it is easier to generate good metrics when you create subcategories that are evaluated separately. Though there might be advantages to these groupings, we also want to draw cautious attention to what

is lost at this scale and how grouped data might seem counter to the perspectives and needs of families and well-meaning teachers.

None of the data collection processes described in this chapter are new. For decades, youth identities and their outcomes in schools have been constructed and parsed into lived differences for students long before they ever even enter schools. Approaches to understanding student performance based on socioeconomic markers or even zip code have been in use for years.

In our experiences working with educators, teachers often strive to work in beleaguered conditions in classrooms specifically because of their commitment to bettering the learning opportunities of their students on an individual basis. Great teachers get to know and build meaningful experiences for the students they work with each year. They offer detailed feedback to students and to their guardians. They are seen to operate at an IH level. Our profession *trains* teachers to do this and it is likely in our human nature to do so: the relationality of seeing and empathizing with the learners in our classrooms makes us better able to tailor our instruction to them.

In recent years, however, the wave of data-informed schooling practices has shifted the ways in which many teachers are evaluated. They are evaluated by group progress. Quantitative formulas like Value-Added Models (VAMs) compare student progress from one period to another and collate this data to determine how much “value” individual teachers brought to a group of students. The new pressures of data-imbued measurement tax teachers and, based on our experiences, often make a school’s atmosphere palpably worse.

What is missing in the descriptions of the purposes of schooling discussed earlier is a particular, key population: the students themselves. The varying and sometimes contrasting perspectives of what schools are for fail to account, at an individual level, for who schools are for. For better or worse, this is where assessment and data often come in. Building from baseline assumptions of preparing students for “college and career readiness” means baseline assumptions of

proficiency and lining students up, academically, to where and how they measure up.

AnSpec helpfully illuminates just how limited our approaches to data and design in schools have been. We identify individual students as a means of comparing their progress to one another or otherwise locating them spatially, cognitively, or socially in comparison to peers. The thing about proffering data through systems that sort and compare is that such practices become shorthand for labeling what characteristics make up the definition of a student. An attendance record, the scores on a reading assessment (like the one mentioned in this book's introduction), a list of disciplinary infractions over the years, and perhaps a grainy photograph uploaded to a school database . . . these do not a student make. They help us recognize that such an approximation of an individual through data points can never be enough. While we may simply see a sliver of a singular identity, the individual, identifiable humans (in AnSpec parlance) are not actually erased when students become metrics.

Considering that the spectra of measuring and designing learning are created by adults, we wonder what happens when we shift the axes of this spectrum and find ways to meaningfully allow authentic youth voices into these spaces. While this wisdom obviously helps ensure that students acquire experiences that may be meaningful to them, maximal productivity does not always equate to maximal joy or meaningfulness. With this perspective, the rest of this chapter looks at how play can be the center of speculative aspirations in schooling.

Speculative Schooling, Data, and Justice

In our description of formal schooling in the opening of this chapter, we intentionally did not talk about the guide-rails to which we are holding fast: justice, joy, wonder, possibility, transformation. To be clear, it's not that these do not exist in schools—much of our teaching careers in K-12 settings were intentionally focused on instilling these feelings within our classroom spaces. The current *purpose*

of schooling—as an interlocking institution with other aspects of governed life—does not hinge on these aspects. However, building from the inviting spirit of la paperson (2017), there are always decolonial possibilities resting within the colonial systems of schooling. How might we awaken them and spring the joints of action toward freedom?

We recognize that kids can (and should) be creative in schools; that—contrary to the perception of play as something that can “provide relief from the strain and tedium of formal schoolwork” (Dewey, 1903)—creativity is central to both the vocational and civic outcomes at the heart of schooling’s purpose as well as to the critical visions of moving these enterprises ever closer to freedom. Of course, there *are* some models of centering play in schools. A lot of them, frankly, are bad. Like our gripes with of educational games, forms of playful school approaches that focus on the data rather than on the people and their experiences are usually no fun at all. If a playful product can be stripped down to attaining points or value within a system or to masking un-fun tasks akin to chocolate-covered broccoli, it usurps the fundamentals of joy and play for meritocracy and productivity.

Although we have devoted an entire chapter later in this book to ways games might shape our interpretations of data and design, we want to emphasize here that play and creativity are tantamount to shifting the perspectives of what might be possible in schools today.

Look at any playful learning environment and notice the chaotic energy and noise. Yes, there are forms of logic and organizing structures at work even in spaces that intentionally focus on not upholding structure. However, it is *hard* to measure what play looks like in these spaces, let alone learning. When we move out the restrictions of schooling, learning does not get easier to measure, but it probably does get easier to achieve. Watch students long enough—the ways they maneuver, innovate, and collaborate in play spaces, particularly younger kids who have not been schooled out of these

playful practices—and you will see robust forms of sustained learning to which schools can only aspire.

Play can uproot the problematic role of data in schooling the bodies and minds of young people today. But such work requires reimagining our data-collecting practices and uses as well as expanding what kinds of data count. Perhaps, as one kind of lens, we might consider how to disrupt power hierarchies and lean toward freer approaches to social interaction. That messy playspace of youth innovation and collaboration—that space we have all inhabited in various contexts in our lives—ought to be central to our students' experiences with their education. How can we attune our relationship to informed meaning making and data metrics to the *affective* domain of these spaces? How they feel and what they inspire in their participants: these are the kinds of ways data might be actionable. Getting to these understandings, however, will require having open and reflective conversations and inquiry alongside young people and looking at these environments as spaces for opportunities to disentangle education from the assessment-driven metrics that currently foreground specific visions of schooling. Admittedly, that is easier said than done; however, if we are serious about working toward data-driven justice in classrooms and schools, it means realigning how data shape what transpires in schools and, indeed, realigning what counts as data.

As lofty as this vision may sound, we want to emphasize that there are precedents for our aspirations. They do not necessarily embody schooling structures at scale; instead, those innovative practices for playful learning that emerge on streets, in social movements, and alongside moments of social rupture echo the promise that we might build upon for understanding and designing with data today. Frankly, we build off artistic and political movements that situate play as a driving force for critiquing and resisting capitalist-driven social forces. For example, we draw inspiration in this chapter's vision of schooling from student-led protest movements throughout

Europe in the 1960s, such as the Situationist International (SI)—a group that might be best understood as a messy conglomeration of artists, theorists, and social activists loosely working toward upending and critiquing wide-scale capitalism. SI drew from Dadaism and surrealism to construct messaging/protest that was equal parts confrontational and playful in nature. Salient to this chapter, the methods employed by SI resonate as familiar countermovements against both technocentric policy and the violence of oppression. Protests, publications, and loose organizing all play important parts in the day-to-day operations of SI. However, key theories that emerged or came into prominence because of SI build up the role of play and ingenuity at work for strategic and social purposes. For example, the idea of “detournement” (Debord, 2020) was a key principle of SI that focused on taking existing media messaging and *turning* it toward new, critical purposes. Detournement is inherently about playing with media, messaging, and audience and working toward particular liberatory ends. Writing about detournement in a student publication in 1966, the members of SI explained the approach as “a form of action transcending the separation between art and politics: it is the art of revolution” (Dark Star, 2001, p. 25). While these approaches to media have continued in the more than half a century since the rise and fall of SI, the emphasis on how to play with media has been increasingly limited in schools (even if there is an acknowledged role that bad faith “disinformation media” play enjoys in fighting actual political democracy today). Rather than suggesting that media literacy should be expanded as an area of emphasis in schools, our perspectives on how detournement might inspire new interpretations of data and its uses in schools mandate critiquing within and across existing systems of data collection.

Playing with the existing tropes of schooling and its use of “big” (and increasingly *bigger*) data in all aspects of the lives of children, how might we disrupt and innovate regarding what is possible with data? What are the playful ways you might spin data toward

imagination? Toward exercises in freedom and speculation with young people? How might you open these questions to an entire ecosystem of people involved in schooling, including parents, custodial and clerical assistants, librarians, and local businesses? How might broad perspectives *about* schooling change the means and purposes of data collection, and how might such integrative exercises be transformative in and of themselves? In Antero's work helping with the design and grassroots efforts to open a school in Los Angeles, it was often the local canvassing, door-knocking, and community-centered dialogues that were most transformative for the long-term envisioning of this work and the participants involved in it. The act of *asking* and the imagination it instilled was often much more important than the forms of data intake mandated as part of the bureaucracy of school operations. A slogan that showed up in an early SI publication is a reminder of how the means and the ends of organizing must be vigilantly interlinked: "If you make a social revolution, do it for fun" (*Situationist International Online*, 1967, p. 24). Justice is certainly serious. However, it must be mingled with the imaginations that US schooling has tried its damndest to squelch in our young people. If we truly want to remake our schools (and our data within them), then play, care, and relationality must root our actions; they comprise the bulk of what makes us human and also tie us to the more-than-human communities within and around our schools.

Toward Just Schooling Futures: A Final Frontier

Earlier in this book, we promised science fiction and speculative education: how do media and/or society help educators and designers imagine new and more desirable contexts of engagement with learning? When it comes to schooling and depictions of it, the storytelling of an imagined tomorrow falls woefully (perhaps dangerously) short. It is shocking that the best-known examples of schooling in science

fiction are pale reflections of existing reality. We can imagine living in spaceships that travel through the fungus-based sublayer of reality (“Star Trek: Discovery,” 2022), but everyone on said ships still seems to have attended schools that required them to take daily catch-up quizzes and memorize the dates of the events of World War 2 and World War 3.

While there are occasionally counterexamples—Le Guin (2012, 2015) is heroic here—much of the world of popular science fiction exaggerates the dangerous uses of data and assessment that are representative of some of the worst schooling practices we’ve seen over the past century. As before, it’s useful to look at *Star Trek*—a reasonably consistent, realized vision of a progressive (or, at least, postcapitalist) future. Schools in *Star Trek* follow a few divergent paths, of which Starfleet Academy is the clearest. Starfleet Academy is, effectively, a model of a US elite university in the 1980s combined with professional practice. There are lectures in a large hall, people are tested on their memory of events through history. Certain professors are mentors, others are didacts. In short, the vision is not far from an old-but-lightly-idealized version of how current universities often suggest that they work. This is combined with limited versions of the diegetic technologies: rather than having a whole class with a simulated Professor Maya Angelou or Isaac Newton, say, they will go for short amounts of time to practice starship maneuvers in a “holodeck” (a fully immersive, tactile simulation environment, in which everything is “real” unless it would hurt the user of the holodeck).

Indeed, some version of the holodeck seems crucial to many visions of the future. Like the holodeck, the Danger Room in the *X-Men* series is a room that recreates and prepares individuals for the world around them. Strikingly, the vision of the world imagined by this room’s design is that the world beyond the walls of the school is a threat to individuals (particularly *mutant* individuals). As its name implies, this room is focused on preparing students for physical confrontations with others—the “danger” here is intentionally foregrounded in the

purpose and pedagogy of the room. As a deeply and problematically designed *simulation* of a world threatening personal safety and liberty, we might consider: What kinds of similar assumptions are embedded within the unnamed danger rooms of schools today? What are seen as explicit and implicit threats in the spaces of state-sanctioned instruction? Lessons of passive engagement with democratic participation (e.g., Garcia & Mirra, 2019; Mirra & Garcia, 2017) or understanding globally competitive engagement in systems of capitalism are key aspects of how most schools function; these are the robotic lasers and swinging robots of the contemporary “danger room,” and we might consider how alternate designs could shift these perceptions. Ironically, many of the ways in which simulations like the Danger Room or the holodeck used to seem futuristic are already possible but seldom used. The starship maneuvers, for instance, seem almost identical to virtual reality (VR) simulations of the same (many currently exist for the home console, both in VR and on screen). It is expensive to toss around a user as a simulation might do it, but it is not impossible. NASA, for example, trains astronauts in just such an environment. One argument as to why these are not more in use is that they do not mesh well with the current models of schooling described at the beginning of this chapter. They feel like “play” (for one)—they do not feel as if they should be graded. As we describe in chapter 6 (about assessment), the grading feels unfair even in the idealized future of *Star Trek*; playful learning cannot be a high-stakes test, almost by definition. Until there is an obvious way either to neuter the enjoyment of a simulation more effectively or find a way to “grade” it in a way that feels fair to pupils, the genre of playful simulation-based learning remains on the periphery.

As we described earlier, school, in its current incarnation, is odd for how it feels so all-encompassing while also being such a new phenomenon. That is a testament to the institution of schooling struggling to justify its existence. Illich (1971) investigated ways that the pedagogical model of didactic schools was inherently oppressive,

inspiring later movements such as constructionism (Holbert et al., 2020) and the learning sciences more generally. Illich's version of "deschooling" feels both remarkably prescient and remarkably dated. He proposed peer-to-peer schooling models in which people would connect in a kind of "[social] peer-matching network" and teach each other. Sadly, that seems like it may have been a bad idea, as contemporary social networks have been shown to harm young people (boyd, 2014). Even when the intention is education, massive open online courses (MOOCs) tend to help the well-resourced most (Reich, 2015), and Facebook creates disinformation bubbles among people who already know each other (Bakshy et al., 2015).

Most versions of future education look less like institutionalized schooling in the US and more like the "apprenticeship models" that both academic and nonacademic trades have used for thousands of years. A notable hybrid example comes from the genre of fantasy which, for reasons somewhat unclear, have settled on a hybrid of Oxford University and trade guilds (let's call this the "magical elite" model).

In many sci-fi scenarios, the data are treated more carefully in corporate-fascist dystopias than they are in the US now. It is notable that, despite the global, fully connected, unlimited computation environment in "Ready Player One," individuals are far harder for a fascist state to find and identify, than Matthew was when he left his keys on a picnic table at a national park (side note: special thanks to the unknown, well-meaning hiker who got them to him).

Illich (1971), in contrast, proposed that freely given personal data made intentionally public would be a revolution for education. It is perhaps ironic that, at the time of writing, we freely make public very personal data for corporations to use and disseminate, and that is a source of misinformation that has drowned out schools. For every biology student taught about the process, value, and epidemiology of vaccination, someone online has claimed that expertise in suggesting that vaccines might turn you into a frog and that it has

probably happened to their cousin's best friend. Both are appeals to evidence, but only one is an appeal to empiricism; they stand on the same legs without any aspect of trust in the expertise afforded by the role of teacher.

On broken schooling Across the examples in the second half of this chapter, we recognize substantial limitations in how science fiction has imagined future models of schooling, broadly. Granted, this is not a comprehensive review of the genre, but we do offer these depictions as generally representative of what popular culture sees as future forms of learning and schooling. What is missing from most of these models is how the students' behavioral data changes how they are taught. In the magical elite model, the teacher is the absolute expert. It is rare that a senior wizard or instructor says, "It looks like the magical-wizard-evaluation-tool says your wrist was pronated 23 percent too far. That's why Rincewind turned into a donkey," or even, "Thanks, young adept, I wasn't thinking of the problem that way." In the electronically mediated and imagined future of living on spaceships amidst alien life, the ways individuals respond to instruction is often blandly in the mode of Skinner (1965). The actual *pedagogy* and the rationale behind why data are deemed important today are not considered.

Despite Silicon Valley's efforts to prove otherwise, systems of effective learning are human-driven. Although current systems of datafication in schools have tried their darndest to move beyond this simple point, these systems continually fail to substantively shift or address the lasting inequities in US schools. Data as it is currently understood and enacted in schools does not "fix" much of anything right now, and that's because it is a bandage for a larger oversight in discounting teachers, the teaching profession, and the undersupported dreams and desires of young people. As students and as teachers, *people*, and our relationships to them, matter. If we know that corporations are good at finding value and extracting the freely given

data from schools, we should probably move toward more fully understanding why this data does little to aid what students do in schools and in their lives beyond schooling.

These are systems that have grown rigid around fixed assumptions about data. But we can change this fact. We can break these systems if we choose. In this way, we are suggesting that we envision breaking apart our intertwined relationship with limited forms of data within schools. From these broken pieces, might we repair schools around healing, playful, and transformative new visions of data?

In his Nobel Prize acceptance lecture (1992), poet Derek Walcott explained: "Break a vase, and the love that reassembles the fragments is stronger than that love which took its symmetry for granted when it was whole. The glue that fits the pieces is the sealing of its original shape." In the same spirit as Walcott's vision of love repairing cultural and historical traumas, how might we glue together new models of schooling that push beyond blasé understandings of tracking and assessment? How can we extend our thinking beyond the rote and banal visions of science-fiction schooling? Rather than simply seek answers in the digital, we must excavate meaning in the analog, human interactions with young people and with teachers.

Interlude: Schools

In this section, we explore a simple code gloss on the stories that in-school data tell. How do they reinforce existing stories? What stories do they hide? As with all the code sections, or, for that matter, as with (quite literally) all communication, ideas or positions are erased, foregrounded, backgrounded, and subject to bias. These are simplistic digital explorations of the nature of complex social interactions. That does not make them less worthy of study or comprehension; ignoring dominant modes of power does not make them go away.

As in all the code in the book, we must start by `IMPORTING` the appropriate parts of the Python language (called “libraries”) so that we can use them as we program. Here, we need: various math functions (basic arithmetic is included by default); the ability to generate pseudorandom numbers (that is, “effectively random” numbers); the NumPy library, which is at the core of most data analysis in Python; and a statistics (and machine learning) package called `SCIKIT-LEARN`.

```
from random import randint,choice,sample
from math import ceil, floor, log
import numpy as np
from sklearn.linear_model import LinearRegression
```

If we want to print out our very simple graph, we need to handle that ourselves. The following “cell” in this “notebook” prints a textual graph given a list of points on that graph.

```
# this generates a list of random numbers (defaulting to 100)
# with a given mean (def. to 50) and standard deviation (def. to 25)
def generate_simple(n=100, mean=50, sd=25, max=100):
    return list(np.random.normal(mean, sd, n))

# this function makes a readable picture in characters
# (a variable with 1 or more characters is a “string”)
# given a graph that is a list of coordinates (“tuple”s)
# for instance, a graph that is [(0,1),(3,4)] includes two points
# (x=0,y=1) and (x=3,y=4).
def graph_to_string(a_graph):
    output = “+\n”
    a_graph.reverse()
    for x in a_graph:
        output += “|{}\n”.format(“”.join(x))
    output += “+” + “-”*len(a_graph[0])
    return output

# if we are drawing our own graphs, we need to scale
# them to the right size. we don't want all the points
# to be on top of each other, say.
def normalize_datum(y, x, bucket_size_y, bucket_size_x):
    return (floor(y / bucket_size_y), floor(x / bucket_size_x))

graph_size_x = 20 # this is an arbitrary number that i thought looked ok!
graph_size_y = ceil(graph_size_x / 2) # graphs often are wider than tall
def plot_simple(ys, xs = []):
    if ([] == xs) or (len(ys) != len(xs)):
        xs = range(len(ys))
    bucket_size_y = max(ys) / (float(graph_size_y) - 1)
    bucket_size_x = len(xs) / (float(graph_size_x) - 1)
    graph = [“ “ for x in range(graph_size_x)] for y in range(graph_size_y)]
```

```

for i in range(len(xs)):
    dn = normalize_datum(ys[i],xs[i],bucket_size_y,bucket_size_x)
    graph[dn[0]][dn[1]] = "*"
return graph_to_string(graph)

```

Now that the preliminaries are out of the way, let's delve into the world of data science. Unfortunately, there is no easy way to explain linear regression without a lot more information; indeed, this is one of those situations in which a little knowledge is more dangerous than none. That said, people use linear regression every single day across thousands of professions. A *linear regression* is an approach for modeling the relationship between two variables (Wikipedia, 2022, among thousands of others). In our case, we will draw a line and the data from two variables and see that a linear regression produces a “meaningfully predictive” model of that relationship (be it strong or weak, positive or negative).

```

max_events = 10

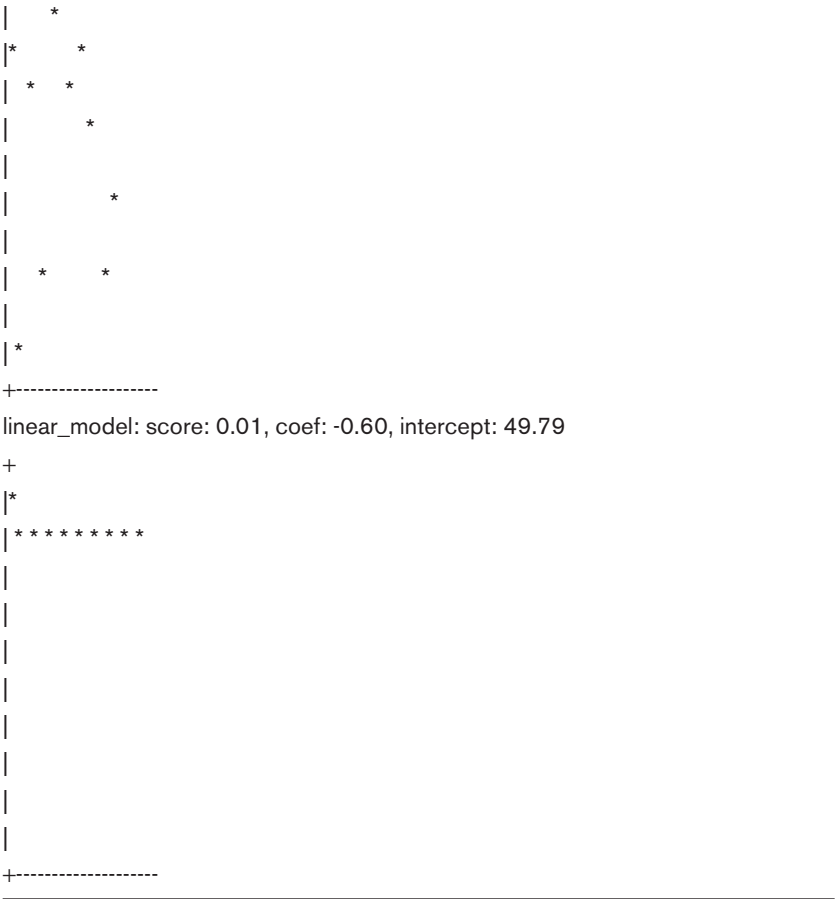
simple_data = generate_simple(max_events) ## generate random data
print(plot_simple(simple_data)) ## plot those data

X=np.array(range(len(simple_data))).reshape(-1,1) ## put those data in the right
format
y=simple_data
model = LinearRegression().fit(X,y) ## perform our linear regression
print(f"linear_model: score: {model.score(X, y):.2f}, coef: {model.coef_[0]:.2f},
intercept: {model.intercept_:..2f}")
# show how we did

pred = model.predict(X) # draw the best fit line
print(plot_simple(pred))

>>>
+

```



Now that we have seen how linear regression is performed, we can play a simple game. The algorithm generates random data, and you tell if it is right or wrong.

The obvious first modification (on your part) would be to input your real-world data. We provide a list (called `VARIABLES`) of possible data you could input; these are variables that real schools use every day. You would be shocked. Real schools and corporations use data that are often this simple (with the addition of your identifying information).

```

print("I will tell you a story about your data, then you tell me if it is correct.")
variables = ["current grade", "actions per minute", "things turned in", "lateness",
"attendance", "other browser windows open"]
salient_variables = sample(variables,4)
real_answers = ["My mom was sick.", "My dad helped me.", "My job made me
come in, so I could not get any sleep."]

X=np.array(range(max_events)).reshape(-1,1)
y=generate_simple(max_events)
model = LinearRegression().fit(X,y)
m = model.coef_[0]
if m < -1:
    judgment = "going down."
elif m > 1:
    judgment = "going up."
else:
    judgment = "staying the same."
print(f"The variable '{choice(salient_variables)}' is {judgment}")
print("What is the real story?")
print("Working only off this data, it might look like: ")
for col in salient_variables:
    print(f"\t{col}")
print("Some stories I might tell are:")
for col in real_answers:
    print(f"\t{col}")
print("Why can't those data tell that story?")
>>>
I will tell you a story about your data, then you tell me if it is correct.
The variable 'other browser windows open' is going down.
What is the real story?
Working only off this data, it might look like:
    lateness
    other browser windows open
    things turned in
    attendance

```

Some stories I might tell are:

My mom was sick.

My dad helped me.

My job made me come in, so I could not get any sleep.

Why can't that data tell that story?

Real lives are hard to contain in a limited set of variables; they make the world much messier and the story, well, less straightforward. It is easier to get mad at a kid because their homework is late. It is harder to be mad if you know that it was late because that kid's mom was sick. Is there a set of variables that makes these analyses humane? How do we interpret them humanely?

6

Museums, Libraries, Informal, and Voluntary Learning Spaces

Libraries are not what you think libraries are anymore. They exceed classic expectations. In many libraries, gone are the days of whispering and diligently searching through card catalogs. From self-checkout stands (with library fines often removed to open access for users) to raucous events for teens and tweens, today's libraries are largely freed of rules that have made them a stereotype of studious silence. Though not universal for all libraries, it is probably not uncommon to venture into your local branch and see patrons engaged in a craft-making workshop; students clustered around a device, animatedly playing videogames together; and children singing, dancing, and listening to storytimes. All these activities are happening simultaneously and with other patrons accessing computers, perusing media, or accessing the information services of on-site librarians.

These practices are not simply a shift to modern times of unplugged and automated convenience (though these are aspects that have dramatically shifted how libraries operate today). Instead, these are cultural shifts that can open and maintain one kind of interpretation of libraries as democratized spaces for information and access. Furthermore, while it may seem that the *rules* of libraries have changed, these

spaces might find even more opportunities for innovation if the data behind them were also to evolve meaningfully. This is not a critique lobbed solely at libraries either.

Museums, libraries, makerspaces, community centers: all of these are spaces that serve important social and civic roles today and that are continually finding new ways to transform in response to changing demographics and demands. Yet, despite this fact, data is too often tied to patron use, time spent within a space, and acquisition/checkout use. These are, of course, important measures. However, they can occlude feelings of joy, the individuals who opt *not* to participate in these spaces, and the ways language practices or surveillance might limit who is able to meaningfully access a given resource. All of this is to say that when the data only reveal for whom we might design, creating the foundations of informal learning environments requires imagination.

We will spend a majority of this chapter focused on informal learning and the environments in which such learning transpires, but, first, we need to interrogate some base assumptions. Before we consider the speculative possibilities of informal learning, let's scrutinize something we, and most researchers, tend to overlook: What is actually "informal" about informal learning? As perhaps an obvious starting place, "informal" stands in contrast to the *formal* contexts of classrooms and schools. Most of the time the label "informal learning environments" acts as a not-so-short shorthand for "not school." While this chapter focuses on the possibilities of these informal spaces, it is worth considering a further question: Why *can't* schools build off these practices? Why must the informal work in these pages live on the boundaries and outskirts of the spaces that are naturally designed with the expectation that all young people will access them?

At the same time, the "informal" label implies that these sites might feel less rigorous. *Relax, these are informal spaces, and the typical rules of schooling don't apply!* Of course, that is not actually the case; as informal as these spaces might be on paper, they are still very much

governed by daily expectations and rules. Our experience working, teaching, utilizing, and studying within these spaces makes clear that traditional data uses in informal settings are every bit as restrictive as in school spaces; the data in informal spaces is as formal as it gets, most of the time. As something of a corollary, there is a whole lot of formality within these informal learning environments. The rules, procedures, and means of access within these spaces are often regimented.

Exploring the meaning of *informality* attunes us to the fundamental tension at the heart of how informal learning environments and their educational spaces are designed, as well as the specific values embedded within them. We engage in this exploration to recognize and uplift the liberatory possibilities in spaces that might be blissfully adrift from the regimented contexts of formality. Also, remember that these are environments that may be maintained through strict regulation and suffocating forms of data collection. For every virtuous public library program, there is a vampiric, understaffed private cram school that exists to turn the money and resources of parents into fodder for an engine of inequity.

This chapter explores out-of-school (informal) education and learning. Parents often consider the safety of, say, an after-school club for their children, but might not consider how, when, and why data from informal spaces is used. Librarians have been and remain careful and thoughtful stewards of data safety and privacy, but sometimes it is not so easy to see when data has real value for children! In contrast, for-profit camps are often sponsored by major companies largely for the data those camps generate. Throughout this chapter, we explore these trade-offs and challenge the nature of informal learning spaces and their applications of current data.

Informal Learning Spaces

Informal learning spaces serve several roles, and they are a crucial element and a core context of any discussion of creative play in education. The ways that informal education is framed in popular media

are notable, as these reflect how it is positioned by institutions of power. Libraries are typically portrayed as boring and quiet, perhaps even borderline-useless for anyone over the age of 10, because they so clearly stand apart from traditional capitalist transactional modes. The wealthy buy whatever books or resources they need, and the library does not charge money for its services. Camps and after-school clubs, however, serve a clear purpose for the wealthy (namely, taking care of children for up to months at a time or on a daily basis). Museums are spaces of wonder, but they are rarely seen as adding anything to society; in movies (e.g., *Batman*, *National Treasure*), they are the locations for parties of very wealthy donors far more frequently than they serve as education spaces, despite the vast majority of the population never experiencing them in this way. In reality, all of these informal environments serve (though differently) as core community spaces for kids, for people without houses and/or jobs, and for people simply looking for places to work or learn. The disconnect between the media representation and lived experience does some work, perhaps, both to ensure that they are perennially underfunded but also to shield them from some of the worst instincts of surveillance capitalism.

Libraries (and their librarians) are a foremost physical site of resistance to this surveillance. Libraries, whether private, public, non-profit, university-based, and/or municipal, have built remarkable safeguards against data spying, and they have been repeatedly punished for it by publishing companies. Remarkably, tools like OverDrive and Libby exist to distribute ebooks without extensive tracking (as far as we can tell). Used to digitally “borrow” books from a local library, these are resources that bring the idea of lending into a digital context. Considering their popularity and distribution models, libraries are charged phenomenal amounts of money per “copy” of ebooks. These are expensive resources for ephemera that cannot be held in your hand.

When we think of the vast array of information available outside of the auspices of libraries, you might wonder if it is necessary to

rely on the archaic model of knowledge preservation in today's digital age. Just look at what is available at your fingertips, through your preferred internet browser. Aside from the dusty academic journals often inaccessible outside of universities (and even those have well-known workarounds), *everything* is available online. And yet, that is not really the point. Perhaps in contrast to some museum archives (which we will get to later), the amount of information available in a library is much less important than the curation of a library to its users. The personalized forms of information, your ability to interact with this information and with experts related to it, and the ways in which such information might cluster community expertise are all invaluable aspects of information and data access that supersede *quantity* for most individuals' needs. These are not practices that have been sufficiently and noninvasively addressed through digital apps and tools. As Martin (2003) describes, even at the turn of the century, the library was considered the every-person's university; a customized education available at one's fingertips is the equitable framing of what the informal learning space can mean.

Importantly, libraries and librarians have played crucial roles in liberatory and justice-centered movements across world history. Within the US we can see important divides in who could access libraries in the era of Jim Crow (Knott, 2017). Likewise, librarians have helped serve as infrastructural support in contemporary movements from Black Lives Matter to Occupy. *Critical* librarianship is an important sister field to the concerns of this book, and we would all do well to work in solidarity with the librarians among us. Whereas contemporary online access to materials is tied to ongoing challenges related to capitalism, surveillance, and hoop-jumping literacy skills, *good* libraries fundamentally democratize access to resources: books, tools, and ideas.

Considering the elements that make libraries so important, perhaps what is the most salient element of informal education to youth is that it is typically situated as a voluntary space within communities.

In a time when there is an increased focus on supporting students' cultural and family backgrounds, few spaces are better positioned than a community center or local library, which are staffed by people whose only job is to help the community. The hyperlocal ubiquity of libraries and community centers makes them stand out in the US. In contrast to the trends in schools, national curricula, and public education for the past thirty years, libraries, museums, and makerspaces often reflect and embody local ethos and histories.

The values and desires of a given community are reflected in the activities, materials, learning, and purposes of these spaces. At the same time, we want to recognize that these spaces are not equally "voluntary" for all members. Children are often foisted into libraries and museums at the whims of adult decision-making. Likewise, these spaces might exclude members based on what languages are privileged within a given space. What might feel like an informal and agency-driven space can often feel stifling for some members of a community.

There is a massive gap, however, between community perceptions of informal education spaces and their possibilities. Most are used as gathering points for access to books and computers (in the case of libraries), viewing of artifacts (in the case of museums), and child care (in the case of community centers). Many such institutions are seen by their communities as static, rather than active and creative, spaces. Recognizing the wide range of these spaces and what they mean, we want to push toward a critical and speculative understanding of the informal.

Critical perspectives on informal spaces There is plenty of important research on informal education focused on access and situated work, which is, as we know, both difficult and necessary. Despite a thoughtful *focus* on data security by librarians, data is still typically used traditionally, often to support arguments for access. Those arguments are crucial and difficult, especially because much of the funding

for these predominantly nonprofit or governmental organizations comes from either public funding (which is fickle and limited) or donations (which take a vast amount of work to collect). The informal learning space is the nexus of a fundamental disconnect between capitalism and social good; these spaces help people, but do not typically make a lot of money. In chapter 7, we look at makerspaces that are, in part, situated in libraries, museums, and community centers (often very successfully); suffice it to say, however, they are not seen as the core mission of most informal education spaces. There is a large amount of research on informal education, but only a small subset of it focuses on creativity or agency.

According to the American Alliance of Museums (Simnick, 2017), the data that are collected trend toward some core competencies: collections, visitor numbers, employee metrics, and resource usage; thus, museum analytics tend toward counting visitors, “dwell time” (how much time is spent at a specific space or exhibit), and various metrics of money flow (e.g., ticket/food/shop sales). These make sense: they are easy to collect, analyze, and interpret. For instance, if your goal is for people to enjoy the museum for a longer time, then dwell time directly reflects progress toward a goal. You might seek to determine whether an exhibit with many smaller displays may be “stickier” than an exhibit with a few larger ones. In addition, if a museum finds that, say, an exhibit abutting a gift shop generates larger purchases at higher-than-normal rates (e.g., a *Star Trek* exhibit encourages people to buy toy starships), that will be considered a success that brings money into the museum more broadly.

There is a natural tendency for these organizations to favor use of metrics that generate resources, and with good reason. To stay afloat, they naturally tend toward the technocratic and neoliberal. That process has many negative implications, but it remains true that these spaces have kept their core mission of public voluntary access to educational resources largely intact over the gauntlet of the past 200 years. Illich (1971), arguing on the side of Foucault (2005), suggests that the

act of positioning educational resources within strictly neoliberal capitalist competitive threat models forces them to orient themselves to self-perpetuation alone. Still, very few (if any) of the people working at museums work there for the cash, as almost all museums run on thin margins. Perhaps because of the core mission, or leaders, or simply the lack of an obviously exploitable massive-profit model, museums and libraries still focus on access to and creation of wonder, learning, and joy for their communities.

The possibilities that inhere in informal spaces make them versatile: they can be made, necessarily, in the form that is required of them at any given moment. This means, however, that they have historically been stretched thin to meet the demands of contemporary forms of surveillance capitalism regarding access to the data of libraries and online spaces. It is hard to argue against generating revenue from selling the data of adult visitors if doing so enables the museum to let local children in for free, especially in an age in which the US has reduced public funding for public spaces so radically.

Data and Informal Spaces

Data doesn't have to be stuck simply acting as a rationale for profit, expansion, and weeding. User experience data can inform transformational work and can lead toward new kinds of possibilities. In this section, we want to offer a productive critique of existing heuristics of data collection as well as a new kind of speculative questioning for our informal spaces.

In the spirit of interrogating the very nature of what it means to be *informal*, perhaps we might question how formal and how visible our data can be (Morville, 2005). Some of our answers may be intuitive: there are always cultural markers embedded in data about demographics of users, checkout rates, or foot patterns (for example), which can be culled from such data. A level of literacy and

prior knowledge is typically required to engage in informal spaces, so this data carries with it an unspoken assumption of intentionality. Likewise, for locations, language, and geographic accessibility, your data speaks to what kinds of people access what kinds of environments in what kinds of contexts. We can use such data for creative expression—for instance, projects in which students create art through data they collect about their neighborhoods (Rogers & Marshall, 2017). Likewise, such cultural markers also offer important caveats to the data regularly collected.

One problem with data is its ability to be anything. To be more specific, anything can become data if we draw such a boundary around it. So, yes, number of people, time spent engaging, words spoken, and so on—these are all familiar kinds of data. But perhaps we might seek to think about what other containers of data might be counted, sorted, and collected: quizzical looks given, moments of elated eruption, times balloons popped in a quiet installation space (probably not enough!). As an exercise, you might choose to think of five arbitrary things that could take place in your informal learning space, from the mundane to the outlandish:

- Someone coughs distractedly
- Identical twins walk into the space looking for directions to an amusement park
- The power goes out, leaving people in the dark
- An animal yips
- Someone sends a text message in the middle of a conversation

We cannot account for the abundance of what the future might yield, but the preceding is a reminder that, if anything *is* possible in a space, those possibilities might function as points of data and could arguably be designed for or against, and they must be regarded with vigilance. What are the boundaries of AnSpec, and how might the butterfly-wing flaps of your imaginative data collection lead

toward systemic change? While we offer silly examples of data in the examples here, we do so with the intent to prioritize questions of joy, of freedom, and of justice. As the situationists remind us, the playful is not solely for amusement. And amusement is not solely for leisure.

Rainbow Agents: In Which We Tried to Use Data Ethically

As one example of how our considerations of data in informal spaces shape our day-to-day work, let us introduce you to *Rainbow Agents* (Berland, 2022; Pellicone et al., 2019). As a game-based museum exhibit (funded by the National Science Foundation) led by Matthew, Maxine McKinney de Royston (also UW–Madison), Leilah Lyons and Steven Uzzo at New York Hall of Science, and Mac Cannady and Eric Greenwald at Lawrence Hall of Science, *Rainbow Agents* asks players to design and tend to a community garden. Fundamentally, the point is to unsettle and recontextualize what counts as computer science, what computer programming is for, and, most importantly, *who* computer programming “belongs to.” Everyone can use computational tools to achieve goals, but if those tools look like “white guy stuff,” then non-white-guys are less likely to feel that it is theirs to use.

In *Rainbow Agents*, players (typically middle school or younger visitors to those museums) write code that is phrased in tropes from video games that those kids will likely find familiar. Indeed, our design process—led by the terrific Quinn Crossley—involves exploring which of these interaction tropes middle-school-aged girls of color might feel most “belonged” and “made sense” to them. Since we know that almost every child in the US (across any demographic categories) plays games, the questions become: “Which games?” and “What features support people in feeling that the games belong to them?”

The rationale is clear: girls—especially girls of color—typically do not feel welcomed by computer science or in computer science

(McGee, Griffith, & Houston, 2019). That said, almost all professional jobs may require some programming in the next few years, and you do not need to be a programmer to program.

As a game placed within urban science museums in diverse communities, there were myriad factors that shaped our design of this game, including consideration of the linguistic, physical, cultural, aesthetic, and/or other resources that the local communities might bring into their museums. Indeed, both sites are museums that serve many students of color. For instance, most students enrolled in New York City public schools will enter the Hall of Science at some point during their schooling career.

That said, most young people do not enter a museum with the explicit intention of playing *Rainbow Agents*, nor do they play it for the entire duration of their museum visit. Ambient discoverability and intuitive game play are fundamental to the design conditions of this space. Unlike, perhaps, coordinated video-game or board-games nights at a library or an evening-long adventure such as a scavenger hunt, *Rainbow Agents* was designed with the everyday user and their wide spectrum of interests and abilities in mind. Considering the amount of time individuals might reasonably be expected to engage with this game, it was designed to create a fulfilling experience for most players within a 10-minute period. By that point, they might experience the recontextualization of computer programming—from, say, their Scratch¹ class in school—as gardening, as care, and/or as collaborative play.

The goals of *Rainbow Agents*, we hope, should be clear—for players, for researchers, and for the broader fields of education and CS. However, salient to this chapter, we want to draw out the ways in which data contributed to the design of this work. First, there are the larger instructional goals of increasing access to CS education learning opportunities for historically marginalized communities. These larger goals are often felt as implicit in a research project's design, but we want to acknowledge the multilayered considerations around

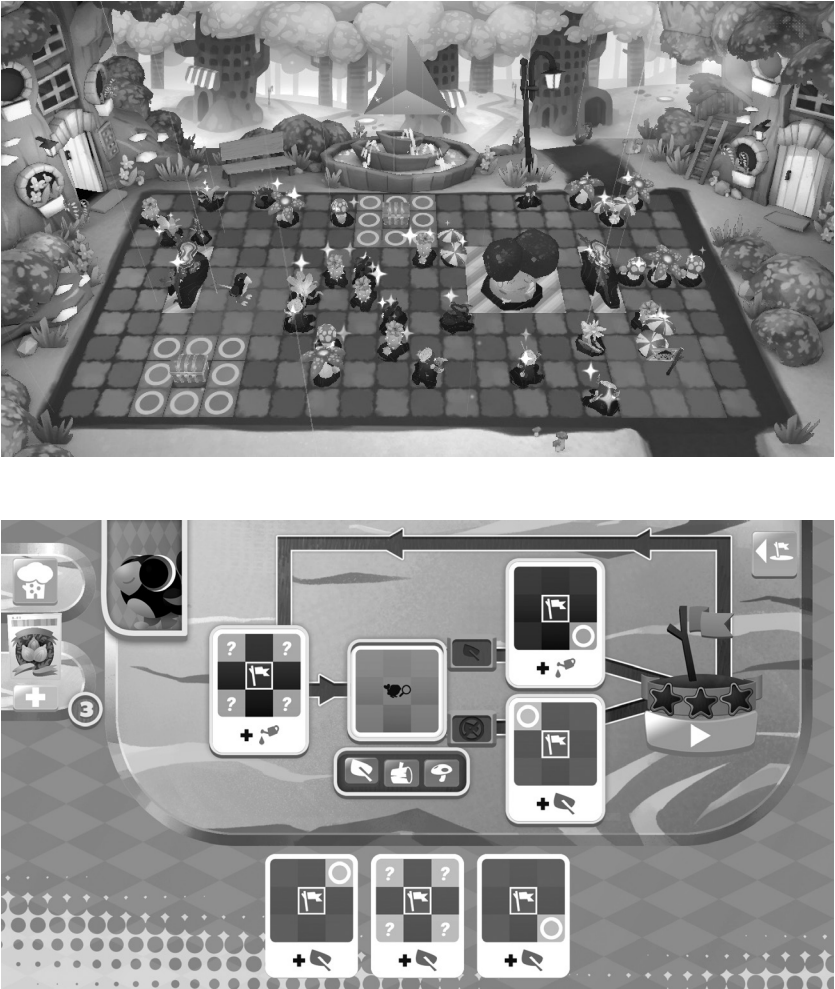


Figure 6.1
Rainbow Agents (top) board and (bottom) programming cards.

access and around the assumptions of why one might want to learn the tools and concepts of CS.

As recent scholarship within the learning sciences demonstrates, the ongoing interest in CS education might be posed problematically as primarily focused on issues of workforce development rather than on issues of equitable distribution of skills and democratization of agency within emerging tech sectors. Vakil (2018),

for example, calls for a “justice-centered approach” to CS education. This vision acknowledges learner identities and the historical assumptions undergirding how and why computational thinking and computer science education are taught within formal schooling environments. Though these foundations are concerns we have addressed throughout this book, we want to emphasize that these theoretical arguments about the purposes and meanings of CS education are not solely about framing data within a project like Rainbow Agents. This section is, on the contrary, designed to draw out the aspects of a research design that might typically be couched in the literature review of grants, proceedings, and research articles.

Speculative Informal Spaces, Data, and Justice

It is odd to see the disconnect between, say, the American Museum of Natural History in reality and in fiction. This difference may simply be demographic, but we suspect it to be rooted in models of capital. Countless examples exist in fiction of museums and libraries—science museums, art museums, history museums, local libraries, major metropolitan city libraries, academic libraries—and, almost without exception, they are inert archives of past glories. Matthew remembers reading *From the Mixed-Up Files of Mrs. Basil E. Frankweiler* (Konigsburg, 1967) as a child and getting lost in the vibrant community of the Met, but out of the dozens of libraries and museums that have made appearances in media like comics, it is hard to find any in which a library or museum is anything more than a repository of ancient goods or a location for a fancy party (similar to the movie *National Treasure*). It is often the case in comics that items in the museums (whether in the past, present, or future) are alien in origin, secretly alive, or incidentally explosive; indeed, across the top 20 examples we found, archived alien items were several orders of magnitude more likely to be found there than were children. Most popular media may not be particularly instructive here.

The tropes of rich and *alien* artifacts held by institutions such as libraries and museums illuminates a kind of settler-colonial lens of how these institutions have functioned throughout their existence and—in many cases—still operate today. Archiving cultural artifacts and the remains of past civilizations is important work. It is also work that has the danger of impinging on the material depictions of existing cultures. Within the US, everything from clothing to actual human remains are frequently contested by indigenous communities who rightfully demand that their cultural artifacts belong not in the archived spaces of museums, but back with the communities and people of which they are a part. So, when we see the magical allure of the unknown and perhaps alien past held in museums beckoning to protagonists in a comic book or film, it reflects our own violent and contested set of archival practices. Even the word *alien* is laden with problematic connotations today. Within the context of US immigration policies, individuals in this country who are undocumented are pejoratively referred to as “illegal” and “aliens.”

One particularly novel use of the library—perhaps written about overmuch—is found in *Star Trek*. LCARS (the Library Computer Access and Retrieval System) is the operating system of the *USS Enterprise* and a just-in-time library in which the concept of access is taken to a logical extreme. Everyone on the ship has access to a vast amount of information, but it is often the case that data carrying sensitive information is not on the ship’s computers. Unlike medical records of the twenty-first century—transmitted freely over the internet—these sensitive records are often limited to a single personal access display device (PADD), which we mentioned in the conclusion to chapter 4. These devices are more like a physical notebook than a tablet computer. That is, the information on the PADD is static and limited to that PADD (though the devices may be wiped and reused).

Nonsensitive information, in contrast, is always available to everyone. If you want to learn about the Battle of Thermopylae, you say, “Computer, tell me about the Battle of Thermopylae,” and it will start

listing information on the nearest screen or simply ask you if you'd like to hear the dates or stories from the battle. This function anticipates later search engines such as Google, and, perhaps unsurprisingly, it suffers from the same problem. If you already know how or what to ask and how to ask it, you have already learned something meaningful about it; the problem is knowing what, how, and why you do not know. Furthermore, LCARS is not situated in a contextual community space, and it does not learn from you. Notably, every time a library is given a modicum of sentience in any *Star Trek* property, it becomes radically evil; this is enough of a trope that even the crew members make fun of its inevitability (as in *Star Trek: Lower Decks*).

This is remarkably apropos for many of the future-looking models of informal education from the 1970s: when they came to pass, they turned evil. Even the extraordinarily progressive, well-intentioned models of education described in Illich (1971) bear a prescient similarity to the Facebook of the 2020s. In Illich's *learning webs*, people form communities unbound by institutionalist models of learning and education (e.g., traditional school) and teach others from their personal expertise. Unfortunately, that has resulted in millions of people whose only expertise may be hate-teaching that vaccines are filled with Jewish mind-control microchips. This eventuality—widespread data sharing connecting people to the most virulently harmful learning webs—was not foreseen. So, does it have to be this way?

Perhaps.

It may be the case that data collection is better avoided than embraced. As the old scholars say, "one must build fences around fences." It would be an egregious act of ignorance if this chapter did not highlight the terrific work done across the information sciences on the dangers of collecting and using data in museums and libraries. Noble (2018) provides an invaluable resource; her scholarship is one of the reasons we wrote this book. Noble's title makes concrete and indisputable the fundamental argument that naïvely reproducing

the statistical patterns of human interaction creates a feedback loop of prejudice, racism, and hate. People who are more explicitly racist in their private lives are more implicitly racist in their public actions; because search engines use those data to shape the information that we see, users are subject to the racism that is amplified by those statistical patterns. It is a nightmare scenario, and it is also the current reality. O'Neil (2016) argues that some of that hateful structuring also exists at an even lower level; it is not simply in the architectures of the search engines, but in the code that underlies all of the systems with which we interact. Her thesis is arguably more hopeful: she suggests that auditing that code and adopting an antiracist lens to the code of the major systems may reveal ways to unravel this feedback loop of hate. It may be the case that the very collecting of any meaningful amount of structured data will inherently lean toward neoliberalism or fascism. Comments from a blind peer review of the proposal for this book suggested that even trying to consider "data for good" was a naïve and potentially harmful act. Certainly, many information scholars have taken that position, and it is consistent with the *Star Trek* position that any library will become evil, given enough data and enough time.²

Toward Just Futures

Evidence of human behavior, when used in good faith, can help us wander (however unevenly) toward emancipation. Looking at the critical work in any classroom, you would be hard-pressed not to see teachers making moment-to-moment, tacit decisions based on the ephemeral data around them. Some information, like test scores, might help calibrate specific kinds of pedagogical approaches, but the quizzical look on a student's face or the consistent signs of uncertainty are also indicators of support that teachers might lend. Likewise, activist movements rely on data in order to further progress. The

most insidious threats to individuals in the US—from gun violence to loss of bodily autonomy to continued land dispossession and blight—are all deeply unpopular initiatives, based on quantitative sampling and survey data. Thus, efforts to push forward new paradigms of living and reform do not simply attempt to foist a minority voice upon the public. On the contrary, the data for emancipation are robust and they are awaiting our harvesting for transformation. How can we situate data in good faith as a tool for emancipation? What data, what evidence can museums and libraries use as tools to help people build agency?

In some ways, informal spaces are perfectly situated to work with communities to build agency. The focus on communities is in itself an act of resistance to neoliberal globalism. Every small-town library and local museum exists as a site of resistance to the homogenization of US culture. If this seems like an extreme statement, we invite you to the small towns of the US where, in many cases, few (if any!) public spaces exist for people to simply *be* free of charge other than on roads or in government buildings, libraries, and community centers.

The resistance, then, might come not from the grand aggregation across millions of libraries but from a focus on the hyperlocality of the information that is coming in. What sets a community apart brings it together, as the adage goes. By determining what makes communities unique, they become closer and more mutually supporting. By focusing on supporting creative work that expresses a community's difference, one can elevate and celebrate it.

This is already the role of many of the small museums that dot the nation, though they largely do so without any technological infrastructure. This is ethically wonderful, but logistically problematic, as they do not then have the tools to resist the encroachment of a new bank or mattress warehouse. How do we build those tools?

Interlude: Museums and Libraries

In this interlude, we are going to use the wonderful, beautiful open data from the Cleveland Museum of Art to generate new, fake art pieces. The idea here is to think about the power and limitations of open data, of historical bias, and of the problems of language in the public space.

This chapter comes with a BIG warning: A lot of art is racist, developed in patently racist societies using racist language. The same trigger applies to sexism, colonialism, homophobia, antisemitism, ableism, and other forms of oppression. We feel confident in saying that this is not the fault of the Cleveland Museum of Art. To remove all art created in racist societies is to remove all art. That said, it is shocking to see how quickly the simple statistical trick shown here will reproduce, say, sexist modes of language, simply because they are so overrepresented through the historical artifacts and their descriptions.

As with all interludes, we start by bringing in all the `LIBRARY` modules that we will need. In this case, we also need to download a separate toolkit of language information about English as a spoken/written (“natural”) language; the use of the term *natural* for spoken/written English language could be another whole book, perhaps.

```
import json # to parse the data format
import urllib.request # to get data from the web
import pickle # the storage format for python
import nltk # "natural language toolkit"
import re # regular expression library lets us search text
from random import choice, random
from os.path import exists # this asks "does this file exist?"
from bs4 import BeautifulSoup # this can turn web text into human-readable
text
from collections import Counter # helpful to create tallies
import string

# the first time we use the natural language toolkit (nltk)
# we need to download the data
nltk.download('punkt')
>>> True
```

Now we need to download the information from the Cleveland Museum of Art's database. That said, we do not want to download all of it every time we want to use it, so we save it to disk in a format that Python (the computer language) prefers; this is called `PICKLE` (and the file ending on a pickle file is, at least for me, `.PKL`).

```
# we would like to only ask for data from the lovely museum once,
# so we need to store it locally
data_filename = "./cleveland_data.pkl"

# if we have not already made a data file, we need to make one
if not exists(data_filename):

    # the wonderful people of the cleveland art museum
    # make a lot of data open and free.
    # read more here: https://openaccess-api.clevelandart.org/
    CLEVELAND_URL = "https://github.com/ClevelandMuseumArt/openaccess
/raw/master/data.json"
```

```
# we need to get the data from them, and this is how they suggest to do it:
with urllib.request.urlopen(CLEVELAND_URL) as cleveland_json:

    # json is the simple and human-readable data format they use
    cleveland_raw_data = json.loads(cleveland_json.read().decode("utf-8"))

    # pickle.dump puts all that data in a file we can use locally
    pickle.dump(cleveland_raw_data, open(data_filename, "wb"))

# just to verify we're using local data, we will only use data loaded from disk
art_data = pickle.load(open(data_filename, "rb"))

# this tells us how many artworks were in that query above
print(f"DATA LOADED: {len(art_data)} artworks.")
>>> DATA LOADED: 64137 artworks.
```

Now that we have loaded our artworks, we need to get the descriptions of the art. We are not going to look at the visual components of the art—just their descriptions.

```
# we are just using the descriptions of all the artworks
# no titles, no artists, nothing.
all_descriptions = [elt['wall_description'] for elt in art_data if 'wall_description' in elt
and None != elt['wall_description']] + \
    [elt['digital_description'] for elt in art_data if 'digital_description' in elt
and None != elt['digital_description']]

# beautiful soup takes the "HTML-like" descriptions and makes them raw text
soup = BeautifulSoup("".join(all_descriptions))
descriptions = "".join([c for c in soup.text])

# nltk does the hard job of turning all the words into a nice sequential list
# you'd think that simply separating by space does the job
# but that, again, is a bias toward simple sentences.
# for instance, it's easy to see how: "You have a cup." becomes
# ["You", "have", "a", "cup", "."] but sentences
# like "Bob's cup is at St. Germain" are harder to parse.
art_words = nltk.word_tokenize(descriptions)
```

Now that we have the descriptions, we need to find a simple way to statistically encode those descriptions. We are using a simple, but effective, idea called the *bigram*; this is how autocorrect historically makes its guesses. What's the most likely word to follow the current warp? Sorry, I meant *word*, not *warp*.

```
# strip out punctuation that makes parsing and generating harder
# note ALL the bias implicit here
# in many English AND non-English texts and names, these punctuation are crucial
# but we are just throwing them away.
letters = set(descriptions)
# print(letters)
unwanted_punctuation = set([c for c in letters if not (re.match("w",c,flags=re.A) or
c in ".,'")])
# print(unwanted_punctuation)
def is_punctuated(word):
    for letter in word:
        if letter in unwanted_punctuation:
            return True
    return False
art_words = [word for word in art_words if not is_punctuated(word)]

# The key to our algorithm is something called a bigram
# Our bigrams are every set of two words in a row.
# "A cat sits." -> ("a","cat"),("cat","sits")
# 'zip' is a command in Python that takes two lists
# and make a new list that groups each of the same-located items,
# e.g., zip([1,2],[3,4]) -> [(1,3),(2,4)]
# so we passed in two equally sized lists of all words in order,
# with the second list offset from the first list by one word.
art_bigrams = zip(art_words[:-1],art_words[1:])
```

Now we can figure out the specific likelihood that any particular word is following another word. We create a big “dictionary” which is a bit like a spreadsheet where our code can “look up” these likelihoods.

```
# now we want to make a big lookup “dictionary” of
# all the bigrams such that if we look up the first
# word of the two, we get a list of every word that might
# follow it.
art_chances = {k.lower(): [] for k in art_words}
for b in art_bigrams:
    art_chances[b[0].lower()].append(b[1])
```

At points, we should check our work. What words follow, say, “ancient”? There’s a handy tool in Python (COUNTER) to count lists and show us the most common ones.

```
Counter(art_chances[“ancient”]).most_common(5)
>>> [('Greek', 50), ('Roman', 41), ('tombs', 41), ('Egyptian', 22), ('India', 21)]
```

The output (everything after >>>) means that: the word GREEK follows ANCIENT the most often (seven times in our data); ROME follows it six times; and so on. This makes sense, so we can move on to generate some new art descriptions!

The idea in the following code is that we want to generate sentences based on those likelihoods.

```

# now we just need to generate some new descriptions
# as you might guess from our very simple algorithm,
# the results will be weird. there's a chance they'll be
# racist, homophobic, and/or any number of other terrible
# things. there's some question of whether that means we
# should allow them to be randomly generated and potentially
# upsetting/damaging or whether specifically excising
# problematic language is erasing the real, colonialist history of art.

# let's make no more than 10 sentences, this is easily changed
num_sentences = 10
for _ in range(num_sentences):

    # we need to start our sentence with a random word!
    prev_word = choice([word for word in art_words if re.match("\w",word) and
    len(word) > 3])
    word_number = 0
    sentence = ""
    # end sentences at a '.'
    while "." != prev_word:

        # this is the crux
        # the next word will be randomly chosen from the
        # list of words/punctuation ("tokens") that
        # follow the current word in the text
        # if "of" follows "book" 80% of the time,
        # then that list (art_chances["book"]) includes 80% "of"s
        # and that should be the word we choose 80% of the time.
        new_word = choice(art_chances[prev_word.lower()])

        # capitalize the first word of a sentence
        if (0 == word_number):
            prev_word = prev_word.title()
        word_number += 1

        # don't put a space between a word and its possessive
        # but do put space between most other tokens.
        sentence += f"{prev_word}"

```

```

if not (re.match("\W",new_word) or "s" == new_word): #punctuation
    sentence += " "

# move to the next word
prev_word = new_word

# a lot of the generated sentences are junk!
# throw away very short ones.
if word_number > 4: # throw away junk sentences
    print(f"{sentence}.")
>>>

```

Planning and beauty, including rites, surrounded by the sculpture as a decidedly personal visual terms" da Firenze on a place, halfway between 1389 and Erlangs focus for Cowan's magnificent decoration of contemplative, but deviated from Heike Monogatari, while her husband is not the empty and the 1880s.

Textile with the inclusion of hours perhaps Cardinal Francisco Jimenez was an established and his head, marches, Genesis, Mexico's frontispiece.

Multicolored acanthus leaves, and enrich learning her friend, the prince, are an industrys fall on numerous occasions and antique manuscripts produced seventeen of intense colors and wife of a in which typically feature a child god for his name because hot milk to echo the right represents makes etchings, but for the rightmost horse races, mundane, was an advertisement reading.

Other urban density of sculptures in its place mats and important oracle at the first to Alexander Bening, the flowers, Lucky charm of steel.

Designed by casting process is linen tunic decorated with Salomon's hand, and decoration is thoroughly modern age style originated by Michelangelo, the artist developed in the Late and Mrs. Samuelson to build it.

Lacquer stand, birds, particularly taken up and the flattened rim.

Over a hallmark of deluxe copies of Burchfields perception.

1,200 degrees from the reproduction in an exposed, monasteries, whose hair that the figure.

7

Games and Learning

Does your family have a game closet? Looking at the weathered and dented cardboard of stacked board-game boxes in our respective homes, we are reminded that analog games *wear* their data on their proverbial sleeves. The requisite copy of Scrabble only stays held together by a combination of staples, gravity, and unachieved dreams of triple word scores. A handful of the boxes are only recognizable from sense-memory, their spines largely covered in duct tape. Looking inside, too, offers lessons of use and preference. Nestled inside the box for Antero's copy of the two-player card game *Lost Cities*, for example, is a years-running tally of the wins and losses he and his wife have tracked for a decade and a half (Antero would prefer not to detail the rather humiliating differential when it comes to his win record here).

Data and games are a multisensory affair: we can feel and see and hear how games have been loved and innovated upon over time. But as much as we are interested in the data that individuals and companies extract from participants in games and other forms of learning, we want to start by considering the data before your own eyes when you play a game. Look at your family's favorite game . . . maybe it is a weathered set of dominoes or *Uno* deck. Maybe it's a

carefully preserved Splotter game or euro-game with all of the components carefully sleeved and maintained in pristine condition. Even the lack of wear in this sense is, in itself, a telling point about players and their desires. What might we learn if we are to feel and play alongside the games we study in this way?

This chapter explores the growing topic of games and learning. During the COVID-19 pandemic, activities marketed as or structured as games took up a staggering and unprecedented amount of student time. We explore how and why that is the case, give real-world examples, and investigate the promise (or supposed promise) of gaming in education. We also provide code for simple games that learners and teachers can build together to take control of how they express themselves and understand their own data. Games represent the imagined and actual cutting edge of learning technologies and data use. One need only look at the complex forms of learning, collaboration, and technical prowess in modern gaming to see new possibilities for design and imagination. Which is why, now, we need to take a close look at the 1980 video game, *Pac-Man*.

***Pac-Man*, Vision of Future Education**

From a purely auditory perspective, a game of *Pac-Man* is a near-hallucinogenic experience. The sounds of pursuing ghosts and chomped pellets is an arrhythmic percussive racket of sirens, squawks, and abstract noise. It mirrors the movement of the yellow protagonist across a fixed screen. In this way, the sound could allow someone with only a passing familiarity with the more than 40-year-old game to understand the context of play. Ghosts have been turned vulnerable and are now the ones pursued; a level has been cleared; *Pac-Man* has been apprehended: all of these can be discerned without seeing the screen. It ain't much, but the sound that exists in *Pac-Man* offers

localized data and feedback about player performance and about the possibilities for advancing in the game.

There is a way of thinking about whole genres of videogames as a manifestation of the interpretation of user data. As you make sense of a game of *Pac-Man*—its sounds, its inputs, its images—something like a story emerges from the data: a yellow, very-hungry protagonist evades pursuers in search of pellets (and sometimes fruit) in a never-ending quest to consume more and to do so at increasingly faster rates. Perhaps it is a parable of capitalism or extreme hunger or the general rat race of always staying one step ahead of the demons of labor. Or maybe it's just a game about maneuvering a blip from one part of the screen to another.

Regardless of the values we might attribute to a game like *Pac-Man* and the ways we are able to interpret meaning from this character (and later the female heroine, Ms. Pac-Man), this is a game where the combination of sounds, images, and tactile engagement with controls drives meaning for players. Whether you're playing it for the first time (a little odd in our opinion) or you are steadily working to best the world records for *Pac-Man*—itself deeply contested and controversial (Kahney, 1999)—each time you play *Pac-Man* you are engaging in a process of learning, responding, and attuning to a given text. As a game, *Pac-Man* offers deep meaning for players, and that learning *can* help transform how players see the world around them. Sure, we could go deep into the hermeneutics of *Pac-Man*'s constructed world, the inherent value of cherries, and the logistics of how *Pac-Man* consumes (literally and metaphorically). Frankly, Wardrip-Fruin's (2020) appropriately titled *How Pac-Man Eats* does a good job at tackling many of these questions. All of them are learning opportunities and worthy of investigation. However, when we talk about games and learning throughout this chapter, we are less interested in how a game might be adapted and used to serve other kinds of lessons. This is precisely the kind of appropriation of youth

culture that, perhaps problematically, runs rampant in educational research. Popular games can get adapted for learning contexts in ways that build on and respect youth interests; *Minecraft*, *Assassin's Creed*, and *Portal* are all well-documented versions of this practice. However, in general, what we focus on in this chapter is how games are inherently tied to learning practices, the ways data drives learning with games, and how we might shape our understanding of research from within and through games.

What Are Games?

One common theme throughout this book is that there is a complex interaction space between choice, play, data privacy, learning, and justice. As such, when we talk about games and learning in this chapter, we are talking about how individuals and groups might consider data and options in front of them in order to take meaningful action. By their nature, games require choices; by many definitions, games are collections of contingent choices.

There are, of course, debates about both the definition of *games* and whether the term “game” even requires a definition. Like all media, games are defined by the way they are used, treated, and regarded by society. If most people consider something a game—even if it is a wombat or a dodgy Victorian lamppost—that thing is (effectively) a game. That said, as phenomenologists have so deftly articulated, sometimes it can be useful to consider a set or archetype in and of itself to figure out *why* people keep calling that lamppost a game.

As far as we can tell, people tend to feel that things are games when participants have agency to navigate some space or set of rules in a way that feels like (or explicitly subverts) progression and does not punish you outside that set of rules. In the growing body of literature specifically thinking about the contexts of games and learning, *Rules of Play* (Tekinbas & Zimmerman, 2003) is a particularly useful

primer for understanding the possibilities of play. Throughout this chapter, we build from their definition of a game as “a system in which players engage in an artificial conflict, defined by rules, that results in a quantifiable outcome.”

The subversion of expectations in games can lead to delight (for some), and the unexpected and our encounters with it are some of the key reasons we return again and again to playing games. You may have spent your childhood with a deck of cards for Spades or a family set of dominoes or even a copy of *Monopoly*. You know that these games themselves may not harbor powerful surprises. But when they are played by a group, what occurs next is never preordained. If you run into a first baseman and plow him over when you have hit a blooper, everybody (except for said first baseman) thinks this is fine (or funny). If you put on cleats and barrel people over on Mass Avenue, everyone suddenly seems very angry (unless said barreled people are wearing Yankees jerseys, in which case everyone claps). As this paragraph suggests, we take games in all forms as useful opportunities to learn from and to learn through. Sports, board games, video games, freemium games on your phone: all of these are games, and they all share similar traits when it comes to what they *do* for you as a player and, inherently, as a learner. They all also contain implicit lessons of learning in context. When and for which elements does expertise at *Pac-Man* afford skill in, say, EAFC 24 or for a pickup soccer game in the park?

What is important to recognize in these encounters with the unexpected and with the definition of gaming that we build upon in this chapter is that, while it seems like anything *can* be a game, there are delineations that are important to our purposes here. Games require constraints. We usually call these *rules*. A baseball *must* be hit with a bat (and not, say, a foam pool noodle), or else you are effectively no longer playing a game of baseball. Unless a different card is preventing it, you must untap lands and creatures at the beginning of your turn in a game of *Magic: the Gathering*, or else you are not playing a

game of *Magic*. You move your hat or dog or ship in a clockwise direction according to the roll of the dice in a game of *Monopoly* if you want to play a game of *Monopoly*. That's how these games work. You might change the rules with other players and, perhaps, go *backwards* around the *Monopoly* board or keep all creatures and lands tapped at the beginning of a turn in *Magic* or try to hit baseballs with foam pool noodles instead, but these are rules that you and other players will agree to, effectively making new rules rather than erasing old ones. This recognition that games require constraints is an important one. As we have discussed throughout this book, open-ended learning environments that encourage play offer powerful opportunities for research and engagement—and games are one form of play. However, unlike free-form play that is unbound by rules, games typically only work if we consider the texture and limitations afforded by rules. These are productive limitations that enable ingenuity for us as players.

Why Games *and* Learning

To state the obvious: *every* game we play offers an opportunity to learn. When you pick up a domino and count the pips, you are evaluating a set of choices, referencing past interactions with this gaming system, and perhaps thinking about the ways your father-in-law is probably waiting for you to fall into his trap . . . again. Going back to *Pac-Man*, described at the beginning of this chapter, each moment of play requires taking in myriad streams of information, such as Pac-Man's position on the screen, where the ghosts are located, the remaining pellets, the rate at which the game is moving (it speeds up from level to level), any fruit that may be around, and the layout of barriers and walls. It may feel familiar and internalized at this point, but this is in-the-moment synthesis and development of the deep knowledge of one gaming environment. No matter how rote a game might feel, each one requires us to act. This is an opportunity to learn. Yes, there are pedantic ways you might choose to play at random to confuse opponents or perhaps abstract examples of games that get played for

you, but these are niche cases that do not help illustrate the general role that games can play in our lives or, specific to our needs here, how we might think about the freedom that games can afford us.

While it might be useful to consider that this chapter assumes that games *are* learning, schooling systems tend to separate the kinds of learning that happen when we are playing games from the kinds of learning that typically “count” in school-based settings. This is a problem. As we explored earlier, these kinds of structures that dictate what counts as schooling are what maintain distance in our quests toward freedom. When we discussed the complex systems that track and evaluate young people in schools, what might be less clear are some of the more pernicious ways gaming has been leveraged against student learning over the past several decades. The emphasis on gamification and game-based learning in schools is a trend that is good at taking the worst (and least fun) aspects of games and mixing them with instructional content in often bland or vapid ways. It is a chocolate-covered-broccoli approach to teaching kids. This is only one way in which games and learning are mixed in the ugliest of palettes in schools. There is plenty of excellent research that covers this in significant detail, including work by Gee (2007) and Squire (2021). In addition, educational games are notorious for and noxious in their tendency to collect massive amounts of student data outside the agency of those students, all the while giving them the illusion of agency within the space of the game. There are things that exist in the liminal spaces of “almost game,” “almost play,” or “almost privacy,” but most of the cases lie well within the spaces of accepted boundaries. We discuss a few examples in the next section.

Data and Games

Building off the framework developed in the first part of this book, we are intentionally hoping that game designers and researchers might take a step back and evaluate where, from whom, about

what, and for what purposes data is collected within educational gaming contexts. We recognize that there are myriad intersecting reasons for how such research plays out. Evaluation (and our assumptions of what ought to be evaluated) plays a central role in our understanding of how data collection unfolds around most educational activities, games included. By mapping the common trends and shortcomings of most approaches to educational gaming, we are hoping to instigate a more intentional conversation about where and how we collect data. Pushing on AnSpec here (as in previous chapters) will help us draw some key themes to build upon and some to background.

IH: Gaming as an Identifiable Human

Most single-player video games assume that you will be playing alone, that you are fine with the harvesting of your data, and that the data will be transmitted back to some centralized advertising database. According to the Entertainment Software Association (ESA, 2022), most Americans—particularly young people—have played a video game recently. Further, most Americans have phones and almost every phone has single-player games on it. The transition to “phoning home” happened reasonably quickly, and not without some controversy. Indeed, the desire that the companies had to sell or use player data outstripped the technology they used to collect it, and they started to use it for piracy prevention. Anti-piracy technologies almost invariably caused problems, locking people out of games that they had authentically purchased, and, for some time, it was common on social media to assume that someone had to have pirated a game for it to be working. The rejection of total data collection and surveillance models of single-player video games is a selling point for some distribution venues (e.g., itch.io), which explicitly advertise that their games are “DRM free” (that is, free of digital rights management). Although this is not the same thing as “surveillance free,” many people treat this label as meaning just that. Not coincidentally,

over the past 10 years, many single-player phone games have gone “free to play,” which means that you can play free for a bit before you must explicitly pay for “gems” (or other in-app purchases). This process profits from players via multiple streams, both harvesting their data and making money from continually charging those players for the ability to keep playing games. If this sounds like the logic of slot machines, that’s because these games seem to be modeled after gambling systems. The popular gaming site Polygon (Kuchera, 2018) has suggested that single player mobile games are almost dead but for “free to play” models. However, services such as Apple Arcade, which includes many games—explicitly excluding free-to-play games and predatory mechanics—in exchange for an overall monthly fee, are opening new models of gaming and consumption. Presumably, like other Apple digital products, this approach does not purely abandon surveillance, but rather limits it to within Apple with some promises not to sell that data.

AG: Gaming as an Anonymous Group Activity

Like IH data, anonymous grouped data is reasonably common in games. Many games, especially games played in public spaces like arcades or museums, do not propose to gather data on any individual; indeed, they could not even do so if they wanted to. It would be difficult, for instance, to differentiate player movements at a mall arcade version of *Street Fighter 6*. Obviously, these games are far less common than they were when we were children, but they persist, and the remnants of arcade culture continue to shape gaming communities and society at large. Arcades (e.g., Dave and Buster’s), movie theaters, and many other public spaces use digital games to draw people in or entertain them while they are waiting, lounging, or socializing. Pinball, for example, has waxed and waned multiple times in the past few decades. These types of games collect data, though the data that they collect might be restricted to things such as crashes, play time or, most likely, the amount of money the game takes in. These events

happen in aggregate, and they might be used, mostly locally, for decisions about which games might be fixed, bought, or moved off the floor. Still, the very act of engaging with a game in a public space is an aggregate grouped act. Their persistence is notable. There is something enjoyable about competing against others in a physical public space (think of the leaderboard of a pinball machine) that is hard to replicate at the global or national or international scale that online games might inhabit. That may explain one element of why they have not entirely vanished the same way as older technologies like telephone booths, despite both objects being supplanted by cell phones.

Less commonly seen by most of the public, augmented reality games (ARGs) offer a terrific example of anonymous grouped games. Born initially from online internet activity (and tied to film marketing), ARGs can be entirely analog (Garcia & Niemeyer, 2017). The simplest example might be geocaching, in which you find or leave hints for people as to where to find interesting tidbits, which the finder replaces with new items for the next player. The assumption is that the anonymous crowd of fellow geocachers fills out the space of possibilities; that is what makes the game interesting. Finding a cache feels simultaneously personal and anonymous. Today, geocaching can be tied to apps and GPS technologies, but at its most basic, these are not necessary to play and attune your behavior as a player to the world around you and the guidance of other, anonymous players. You might find an interesting book and leave another, or you might find a note from someone who's been there before and leave another with your name.

AH: Anonymous Individuals, Games, Gambling, and Education

In sharp contrast to the bombast and collective participation of arcade games that require the presence of other players, single-player video games have almost completely vanished from these spaces. When it comes to gaming in public, gaming has embraced the social. It is hard to think of a place where it would be expected for you to

be playing in public in a way that doesn't interact with anyone else, at least in most Western contexts. This is likely because most Americans have phones or computers on which they can play games; if you want to play alone, you now do it alone. In this way, the number of people idly playing videogames by themselves in public has exponentially risen, but they do so hidden from the gaze of others, perhaps while waiting for public transportation or for friends to arrive. This is done casually, privately, and outside of the quarter-consuming contexts of spaces designed for gaming.

Most people who want to play a video game alone do not tend to go anywhere to do so. That said, perhaps at the outer boundaries of what counts as a game, you find the slot machine. The slot machine is specifically a game in which no one cares to harvest your data because they are making money not from your data, but from you. If there's any notion that you might be less likely to put money in the machine should it collect your data, they will avoid doing so. The experience is also aggressively individual. If there are multiplayer slot machines—which there might be, though we can find little evidence of any—they are rare. Instead, the deal that these machines offer you is that they will not ask anything of you if you pay them money directly. The games themselves are not fun, and there are few (if any) choices. However, there is the thrill of winning, rare as it may be; the choice that you make when you play a slot machine is a decision: "How much am I willing to lose in order to enjoy the potential to win?" At the moment, slot machines are effectively anonymous, despite being electronic and networked.

If gambling occupies a space at the periphery of gaming, team sports have historically represented the set of games of which video games were the periphery. Team sports exist in almost every part of the United States; they are a core activity for many Americans, whether watching, participating, or simply reading about them. As a nation, the US loves teams categorically. When players across professional sports occasionally blurt out an "I'm in it for myself"

statement, they are branded a heel or a villain. It is understood that if you play on a team, you play *for* the team. In the time you've taken to read this chapter, there have likely been interviews in which a star player, who may have been largely responsible for a win, states or suggests that it is "all about the team." This perspective carries from Little League to the NFL. Metrics of and data about *teams* are repeated endlessly. A team's seasonal performance and golden ages of a team are shared by fans. It is an issue for more focused studies than ours as to why it persists, but the team as an identified unit has a set of data associated with it and fans show loyalty to those data—even if no players, owners, resources, buildings, or managers are shared over the course of decades.

Speculative Play, Data, and Justice

Considering the wide array of kinds of play that afford different kinds of data, it is frustrating that educational gaming data are so bad. Our collective emphasis on assessment and myopic visions of knowledge have crowded out varieties of games and the ensuing fun they could provide. As two educational researchers who spend a lot of time thinking about, studying, and creating games for learning, perhaps our cynicism at the state of this area may seem surprising. However, this cynicism is born of seeing far too many predatory approaches to engaging students and teachers.

Video games, as we have seen, tend to be more of a signifier of what is called "social configurations" or "frames" (Goffman, 1974) than they are a specific formal representation. A game is less a specific set of criteria and more a way of interacting with people. If you kick something at someone while smiling, you are playing a game; if you draw on a chess board, you are not. The things that become games tend to revolve, in some ways, around how your choices are

encoded into input data, whether the game is a tabletop board game, a sport, or a video game.

To start, positioning your choices as “mutually enjoyable” can make a lot of things into a game, if that proposal is accepted by other people. It can then become collaborative, competitive, or cooperative—you might be working together or against each other—but, in any case, it must be understood either as the specific instance of something well accepted to be a game (e.g., boxing might not look very fun) or something mutually enjoyable (e.g., kicking something to someone can be threatening or playful depending on context).

What is notable is that the one thing that turns many things into games—whether or not they share any formal similarities with “things believed to be games”—is mutual data. When multiple beings exist in the mutual space, then scoring things or even just keeping mutually agreed data records (such as a log) makes many things into games. Try it: Do something mutually acceptable to someone near you—maybe say “What do you want for lunch?”—and then when they respond, follow it up with (for beginners): “It’s not 21 to 16; you’re winning” or (for experts) “That’s two reds and a blue for you, but I’ve got seven green—I am catching up.” This is now a game; this is the magic of data. Indeed, Boluk and LeMieux (2017) play on this more eloquently, giving you a *score* as a reader, thereby gaming game-based learning.

Toward Just Futures: Subversive Play for Liberation

A few questions that emerge from considering the possibilities of play are these: Who gets to create the mutual data? Who gets to control the mutual data? How manifest and substantive are the choices that a “player” can make? A truism we are reminded of when it comes to games and data is that “the house always wins.” In the literal sense, casinos may pay out occasionally, but they structure the rules and contexts of the games such that they always end up making money

in the long term. More generally, it suggests that when you make the rules—especially in scenarios in which the context both affords you power (e.g., casinos and capitalism) and gives you the power to both enact and enforce the rules you’ve made (e.g., security guards and ideology)—you will win. You do not necessarily need the full weight of the state to enforce the rules of a board game, but gaming requires that the people playing afford you opportunities for the power of setting the rules.

When that power interacts with the other factors of games mentioned earlier—addictiveness, fun, collaboration, learning opportunities, and local choices—the water grows murkier. That said, these factors—perhaps even “fun” and “addictiveness”—all reflect what many people consider a best-case scenario for schools. This suggests the open question with which many people in game-based learning research still struggle: When is it ethical to use games instrumentally in schools? Is it ethical to get kids “addicted” to math games or “tricked” into enjoying problematic or rote content if the result is that they become very quick with basic arithmetic or reading? If we believe that books can convince someone of something, we have to believe that games as a medium must be able to do so as well. This must be at least trivially true, because books can be “phrased” as a game, and it would be a hard argument to make that they lose all their rhetorical power in that scenario. Bogost (2008, 2010) makes the opposite point: in fact, games *gain* further rhetorical power through choices.

What are the ethics of the real and current scenario in which students are “convinced” to share sensitive data to play educational games? As there is very little oversight of game data logging by private companies (outside of federal guidelines, where it is hard to prove a violation without direct evidence), we have essentially decided to trust major educational technology companies to use our children’s data responsibly. Some of these “games” are only framed or marketed as such; they might signify choice but, in the end, afford basically

none of it. Students are now, by and large, are savvy enough to know the difference, and the conflict between diegetic signals of choice and actual meaningful choices stands out to pretty much everyone involved. (Your days are numbered, “game-like” videos on rails.)

Games are much more common now in schools than they were a few decades ago; the independence of being able to choose one’s content and work with friends to tackle it was, basically, unthinkable in the massive public-school framework then. In this spirit, there is something transgressive to be found in introducing designed experiences that prioritize both student choices and student collaboration and cooperation over regressive models of school. Now it is common enough that teachers, parents, and students feel free to complain when it is absent. Unsurprisingly, it turns out that providing students with opportunities to make meaningful choices about how they spend their time is, on the whole, a good thing.

Interlude: Games

This interlude presents a short “game” that plays with the idea of logging. In this game, you use the log created by your typing to play the game. All play happens through logs. This idea is perhaps more “surface-level clever” than deep or trenchant, but it does force the player to focus on what is being logged, why those logs are happening, and their constituent parts.

As with all interludes, we start by importing every `LIBRARY` module that we will need throughout the program.

```
from random import choice, shuffle
from IPython.display import display, clear_output
from time import sleep
```

In this game, you are playing tic-tac-toe with logs. Perhaps the trickiest part of programming tic-tac-toe is figuring out whether the game has been won already. A human can look at a board and see if there are enough Xs or Os in a row, but a computer needs to “walk” through the board row by row, column by column, or, most tricky,

diagonal by diagonal. If this were a guaranteed 3×3 tic-tac-toe, we could just list all possible winning/losing/tying boards and check the current board against them, but we are making a variably sized board, so we cannot do that.

```

BOARD_SIZE = 4 # 1 is the smallest board, the biggest is limited by your screen
start_board = "."*(BOARD_SIZE*BOARD_SIZE) # the board is actually just a string
of periods

# these are helper functions that translate between the x & y and the internal representation
# remember, the internal representation is just a simple string
xy2i = lambda x,y: x + (y * BOARD_SIZE)
i2xy = lambda i: (int(i % BOARD_SIZE), int(i / BOARD_SIZE))

# drawing the board, labeling the axes
def a_draw_board(a_board):
    # the "reversed" just makes it look more like cartesian coordinates
    # like (0,0) in bottom left corner
    for j in reversed(range(BOARD_SIZE)):
        print(str(j),end="|")
        for i in range(BOARD_SIZE):
            print(a_board[xy2i(i,j)], end=" ")
        print()
1 print("-+" + "-"*BOARD_SIZE)
    print(" |" + " ".join(list(map(str,range(BOARD_SIZE)))))

# if i flip the whole board to its horizontal mirror to check for winners,
# it means i can do less work overall. tic-tac-toe works in a mirror.
def ab_hflip(a_board):
    output = ""
    for j in range(BOARD_SIZE):
        for i in range(BOARD_SIZE,0,-1):
            output += a_board[xy2i(i-1,j)]
    return output

```

```

def a_board_won(a_board):
    # horiz in a row [[(0,0),(0,1),(0,2)], ...]
    horiz = [a_board[xy2i(0,j):xy2i(BOARD_SIZE,j)] for j in range(BOARD_SIZE)]
    # vert in a row [[(0,0),(1,0),(2,0)], ...]
    vert = ["".join([a_board[xy2i(i,j)] for j in range(BOARD_SIZE)]) for i in
range(BOARD_SIZE)]
    # diag in a row [[(0,0),(1,1),(2,2)],[(2,0),(1,1),(0,2)]]
    diag = ["".join(t_board[xy2i(i,i)] for i in range(BOARD_SIZE)) for t_board in
[a_board,ab_hflip(a_board)]]
    all_combos = horiz + vert + diag # it has to be one of them!
    for combo in all_combos:
        if combo[0] != "." and combo == len(combo) * combo[0]:
            return combo[0]
    return False

def a_board_complete(a_board): # no moves exist if there are no empty
(i.e., ".") spaces.
    if not a_board_won(a_board):
        return not any([c == "." for c in a_board])
    return True

def a_play(a_board,x,y,player):
    a_board[xy2i(x,y)] = player
    return a_board

```

We need to test our implementation of tic-tac-toe before we implement the “game” element of the, uh, game. The following cell simulates tic-tac-toe, playing both sides until a win or a draw.

```

def valid_xy(x,y): # is the move on the board?
    return x >= 0 and y >= 0 and x < BOARD_SIZE and y < BOARD_SIZE

def insert_piece(a_board, index, piece): # this adds a piece to the middle of the
board
    return a_board[:index] + piece + a_board[index+1:]
# for our own sanity, we need to test out our tic-tac-toe

```

```

# implementation. this function simulates tic-tac-toe.
def a_sim_ttt():
    sim_board = start_board # start with an empty board
    player = "x" # ttt starts with x
    while not a_board_complete(sim_board): # end when the board is complete or
        won
        clear_output(wait = True) # to look nice, we want to animate the simulation
        valid_plays = [i for i in range(len(sim_board)) if "." == sim_board[i]]
        # where can we play?
        shuffle(valid_plays) # randomize all possible spots; do not pick, say, the
        top left
        sim_board = insert_piece(sim_board,valid_plays[0],player) # pick that
        random spot
        if "x" == player: # switch player here now that a piece is inserted
            player = "o"
        else:
            player = "x"
        a_draw_board(sim_board) # draw the board
        sleep(0.25) # wait for a quarter second so we can see the animation

a_sim_ttt()

>>>
3|x.xo
2|xox.
1|ooxx
0|oox.
+-+
|0123

```

This is our game. In this game, we type something, it is logged, and that last log entry is parsed to generate an (x,y) coordinate and either an x or an o play. It's . . . hard. That said, the code contains all the answers to how to solve it. The rhetorical value is debatable, but the pedagogical value is in thinking through how to generate logs, how to modify code, and the joy of solving this little conceptual puzzle.

```

# you generate log entry
# every log entry maps to a "xo."
# then you place that piece
# the game is to understand map of log entry to x/o/.
# so you can win as x or o

def secret_piece(msg): # do not look
    return "xo."[ord(user_msg[-1]) % 3]

def secret_x(msg): # look away
    return (ord(user_msg[0]) % BOARD_SIZE)

def secret_y(msg): # nothing here
    return (ord(user_msg[1]) % BOARD_SIZE)

LOG = []
quit = False # are we done?
game_board = start_board
user_name = input("What's your name?") # Just to be nice
while not quit:
    winner = a_board_won(game_board)
    user_msg = input("Type here (q to quit):")
    if user_msg[0] == 'q': # we have to let people quit somehow
        quit = True
    elif winner: # or end the game
        LOG.append(f"WIN: {winner} wins!")
        quit = True
    elif len(user_msg) < 3 or len(user_msg) > 128:
        LOG.append(f"ERROR: Please type between 3 and 100 letters and/or
        numbers.")
    else:
        piece = secret_piece(user_msg) # this code must not do anything
        sx = secret_x(user_msg)
        sy = secret_y(user_msg)
        LOG.append(f"LOG: {user_name} typed {user_msg} which generates a
        {piece} at ({sx}, {sy})")
        # we have now added to the log
        if valid_xy(sx, sy): # and we will add the piece from the log
            game_board = insert_piece(game_board,xy2i(sx,sy),piece)

```

```

    else:
        LOG.append(f"ERROR: {piece} cannot be placed at ({sx},{sy})")
    clear_output(wait = True) # make it look kind of animated
    a_draw_board(game_board) # draw the board
    for line in LOG:
        print(line) # print the log (cleared every turn, so we need to reprint)
    sleep(0.25)
>>>
3|. . .
2|. . .
1|. . .
0|. . .
+-+
|0123

```

8

Making, Creative Learning, Technocentrism, and Hope

Much of the work in this book comes down to supporting the creativity that is too often institutionally bled out of students. We have focused on how to provide spaces and opportunities for students to express themselves through their learning in ways that are benefited by positive perspectives on data. In the end, learning is about affording students agency by giving them the space and teaching them the tools to express themselves. In the past 10 or so years, a *maker movement* has sprung up to enable kids to create with code, where they can try out 3D printing, electrical engineering, mechanical engineering, and more. In some ways, the maker movement has, by and large, afforded that agency to those children who are and have been otherwise supported in these domains by their parents, teachers, and community. Making can be technically difficult—even dispiriting—for adults. For every example of kids with resources simply getting more resources, there is an example of a school makerspace, or a library makerspace, or a community center with a creative lab for making video games that is designed to explicitly support minoritized youth. In particular, the work of Kafai and Peppler (2014) has been crucial for seeing that making is not a boys-only activity focused on creating killer robots (though it

certainly can be that) and that technological or technical creativity is not restricted to classically masculine-coded pursuits.

As much as we see the possibilities in these broad spectra, we also recognize that there are a lot of making practices that are not perceived as *making*. In this sense, there is a degree to which some technical pursuits are given different names based on how administrators perceive them. For example, hip-hop production is an extremely technical pursuit, but it is primarily structured to appeal to young men and boys. Similarly, textiles and weaving are forms of making that are coded as being for young women or girls, regardless of their technical (or aesthetic) interests. As a result, the framing of these as maker-included pursuits is often ignored. This is not a question of marketing or branding; it is a question of equity. Who is considered a *real maker*? The prevalent stereotype that only the “boy stuff” is technical enough limits social considerations of intellect, ability, and the possibilities of transformative schools for social, civic, and financial purposes.

What Is Making?

There is robust scholarship examining the intersections of learning and hip-hop (e.g., Adjapong & Emdin, 2015), but the politics of the intersection still plague the boundaries. Is it *only* racism that means “Hip-Hop Ed” is not typically thought of as maker education? Would it diminish the incredible work of the Hip-Hop Ed community (e.g., Ladson-Billings, 2014) to lump that subject in with positivist glosses on traditional engineering education content? Alternatively, is maker education a diminished form of Hip-Hop Ed, in the sense that it can be making with some cultural relevance stripped out?

As we dig deeper into the speculative and justice-driven possibilities of making and creative technology, we want to recognize two underlying tensions: the missing scholarship that should be a part of the historic work in this field *and* the overly-endorsed assumptions

that digital tools, even if they are meant to harness young people's creativity, are not the long-term solution to nondigital inequities that plague school systems and society writ large.

When we look at unique forms of making that young people encounter, engage in, and “geek out” about (Ito, 2013), we find that the kinds of activities that might be considered making are as unique as the kids involved in them. It is feasible to consider choosing toppings at a fast casual restaurant as a making activity.

However, if nearly *anything* could be considered a kind of making activity, how can we find a way to foreground making that will support or enable new perspectives? Is reading a book on the impact of anti-Blackness in the US and subsequently tweeting about it a form of making? It certainly has the possibility to foster new perspectives. In contrast, is learning how to optimize your C code a form of making if it doesn't change your perspective at all? Is an architect's drafting of the specifications to construct a bridge a form of making?

Such questions are semantic (at best). The bounds of the term do not matter so much as a recognition that the term carries different meanings for different people. We will not resolve a definition in this chapter, but instead will focus the question more tightly: Can (and, if so, how do) data support creative, technical, expressive work that enables new, just perspectives?

This chapter treads a funny line: Matthew and Antero believe in the power of creative expression. Plenty of theoretical and empirical work exists that justifies that position, but there is a clear positionality question: is there a tendency to imagine that the things we *like* will generate a positive future? It is possible to argue that creative, technical work in education will be inherently technocentric from a Foucauldian perspective, and that working in sexist, racist, neoliberal traditions merely replicates those structures of power? Indeed, Apple (2004) argues that whenever the focus of an education is *production*, we should be wary because we are being groomed as the product of capital. That the trend in schools has been to add makerspaces, and that administrations

seem broadly amenable to the idea, might suggest that those administrations see things like job preparation (rather than, say, civic education) as the chief goal, even with students as young as grade school. (Rhetoric from computer science [CS] education, regardless of sociopolitical or theoretical orientation, cannot help but mention job preparation; based on personal experience, almost every student, parent, teacher, and administrator asks about it.)

One rebuttal hip-hop education puts forward is that maker education can be antiracist if you are explicit about making it antiracist. Eglash et al. (2021) have done some excellent work here, but it is not yet the mainstream push of the subfield. It is also relatively suspicious of data as a subfield. At last check, Google Scholar has only a page or less each for searches that include either “anti-racist” or “social justice”; some version of “maker education” or “constructionism”; and some version of “data science” or “learning analytics.” Some of those hits are from the authors of this book, and most of the rest are from people we have already cited by this point in this book (e.g., Eglash et al., 2021; Payne et al., 2021; Reynolds et al., 2019; Turakhia et al., 2022; Vakil & McKinney de Royston, 2022; Weintrop et al., 2020).

Can we take a broader data and justice perspective on making?

Data and Making

This is a good excuse to turn back to AnSpec to evaluate how, when, and where data is being used in creative endeavors. There is, perhaps, an assumption that a child’s hand turkey outline¹ is the last vestige of presurveillance. This may be why few scholars are looking to explore the space.

AH: Anonymous Individual Making

Graffiti makes a better example than a theoretical hand turkey. It is designed to be both anonymous and individualized: simultaneously personal, connected, and untraceable. People work hard to improve,

and they might occasionally work together, but if you are traceable, you can no longer work in the space. In some ways, graffiti is a hope for humanity. People engage in it to better themselves, create art, and spread their message without the promise of financial or personal gain and against the threat of legal consequences. Graffiti is therefore, to some extent, an example of learning for learning's sake.

It does not go without saying that graffiti is almost universally recognized as a point of resistance, whether positive or negative. Most movies, TV shows, news broadcasts, or video games that feature civil unrest take pains to show the “INVADERS GO HOME” or other graffiti messaging on the main square; shows about urban poverty linger on graffiti that signifies gang warfare; and it is almost impossible to see any representation of the New York City of the 1980s that does not include a subway car awash in color.

This chapter is not an argument to join a graffiti crew or tag the Austin MetroRail so much as an argument for the notion of annotation in making. Kalir and Garcia (2021) wrote an entire book on that argument, so we will not rehash it here, but the “data” take is clear: creating traces influences later interpretation. Those traces need not be identifiable (and, in the case of graffiti, probably should not be, for the tagger's own safety), and they are each a teachable moment of resistance (Avramidis & Drakopoulou, 2012; Eldridge, 2013).

IH: Identified Individual Making

Most making activities for education and learning might engage individuals in something like “coding” or electrical engineering or textiles. Textiles, code, and gadgets exist aplenty, so the point is *specifically* to experience the joy of making something that feels “more like you” than any pre-existing product. The aforementioned electronic textiles (Kafai & Peppler, 2014) are a good example of this. These textiles enable people to express themselves through creative activity that is distinctively individual and marked, and they are also quite personal. The technology is possible to “assess” in a classic mode, but it is quite clear how deeply that misses the point: it is unlikely

that students will wear even the most technologically sophisticated creation if it sacrifices significant aesthetic value. However, students are likely to work quite deeply and thoughtfully on clothes that they plan to wear. In practice, we have solid empirical and theoretical evidence that this is so (Peppler et al., 2016a, 2016b).

IH work can itself be resistance to sexist technocentrism. For example, Buechley (2016) and Blikstein (2013) show that learning opportunities that are forms of personal expression can be quite powerful. That said, personal expression as data makes a tricky argument: what is data that shares few features in common? There is a natural temptation to reduce it to a lowest common denominator: the code that makes a shawl show a message, say. This is likely a misstep that reframes the personal and humane as a purely technical experience and assumes that what is valuable about the experience is the most technocentric subset of that experience. It rejects the values of the activity and substitutes others.

This highlights (perhaps late in the book) the value of IH data as *difficult* data. Often, IH data is something of which to be careful, but, in this case, it is data's very individuality and idiosyncrasy that make it hard to assess or process. A tweet might be just as personal, but it is encodable; a scarf that glows per the local weather forecast is very hard to compare to a backpack that recites lines from song lyrics. Matthew has done work (e.g., Berland et al., 2015) in which he evaluates the idiosyncrasy of student program code as a goal; his team used these data to help the teacher help students find potential partners. In this study, the IH data was used not as a means of grading or evaluation but as a tool to increase collaboration and help teachers with a minimally invasive classroom tool.

AG: Anonymous Grouped Creativity

In many anonymous creative group activities—such as people singing along at a concert or leaving locks on the love bridge—the point of the activity is to be part of a crowd and to leave something creative

behind in aggregate. Anonymous group creative work can make up some meaningful facet of life in a city; every day, city dwellers pass by any number of elements of art, music, or speech. These stimuli jumble together and become the noise of the city: horns honking a tune, marching bands, and street preachers. One could argue that these things are not anonymous at all—that it is possible to determine the identity of the people who make the buildings, the house decorations, and so on—and it may be the case that functional anonymity will disappear as technology improves. That said, you could walk up to a street preacher, and he may choose to tell you his name, but that is his choice and, without robbing him of his identification documents, there is no guarantee that the name that he does or does not give you has any relationship to his experience. The same is true of so many of the musical or lyrical or verbal components of walking around New York City, Boston, or London. What could be a more salient anonymous group creative activity than a spontaneous “second line” marching band parading through the heart of New Orleans? Anyone can join, anyone can play, players and marchers come and go, but the music carries through; it is not attributable but represents in a tangible way the culture of the city.

A labor union can be an example of data as action, on an aggregated spectrum that can range from fully anonymous to fully identified. Although the identity of individual union members can be determined, the values of the group are group values. Relative anonymity in the union is power; members can speak and act as thousands when interacting with those in power. The union itself can use data to find and leverage potential new members, donors, or political actions. However, the identifiability of potential organizers is a lever for an antagonistic boss; while it is technically illegal to fire someone for union organizing in the US, it is so easy to fire someone that it is wiser to use anonymity as a tool.

IG: Identified Group Making

Many public makerspaces serve as mini art galleries for the creative work that happens in them. There are dozens of examples of makerspaces that hang metal work, laser-cut art, or LED winking electronics from walls and the ceiling. They typically have some set of names attached, but we have yet to see one where everybody's individual contribution to the creation of some electronic gewgaw was spelled out explicitly. The objects are created, exhibited, made, and serve as an implicit assessment of the kind of work that is possible at that makerspace; they signal the kind of thing that you learn to do by spending time there. The possibility space is attributed to some combination of all the people, materials, and knowledge in the makerspace. In that sense, there is something beautiful about showing off the broken and half-finished—but still “cool”—projects. There is something freeing in a makerspace that does not simply exhibit the very best projects, but also the failures, sidetracks, and weird ideas. On a trip to a makerspace not long ago, there was an example basketball hoop made by a group of kids that displayed both how many baskets had been made and the average speed of the ball as it entered the basket. It really did not seem to work correctly, but it was both generative and welcoming to kids precisely because it looked like a mess. The kids exploring the space with me had many questions about it. It was very clearly made by kids, for kids, and you could (presumably) ask them questions if you emailed the addresses that were taped to the backboard. It was made visible in the space because many would-be creators might be tempted to try to make their own version. The project sent a clear message: things you are interested in are here, you can do them, and they don't have to be perfect. That is a fantastic use for data.

Speculative Making, Data, and Justice

Perhaps because it does correspond to capitalist modes of production and progress, maker/arts education pops up in an overwhelming amount of speculative fiction. The act of creating speculative fiction is itself a technical and creative act; it is most prevalent as a simple reflection of its medium. That said, the contrast between “what counts as education/learning” and “what counts as child labor toward creative output” is curious and worth exploring. Disney’s *Big Hero 6* (Hall & Williams, 2014) imagines a school as a sort of technocentric, corporatist MIT Media Lab for children. The presumption is that this ragtag group of youth have some “genius” that enables them to do mechanical, electrical, and computer engineering extremely quickly and uniquely. This conceit springs from an extremely long line of similar themes, in which the superhero-protagonists are children who somehow invent something truly unique and immediately usable in practice. (One might argue that David’s remarkable anti-Goliath sling is an example.) Spider-Man (e.g., Watts, 2021) is a classic example of a teenager who can (in some stories) barely pass his high-school classes, but who is able to create an engineering masterpiece in his “web shooters.” Notably, this technology cannot be replicated by anyone else (they are a personal expression of his new powers) even though there is (typically) no point in the comics at which he learns the skills and knowledge to do this. In some versions of the Spider-Man mythos, he learns from Otto Octavius, at Empire State University, or from a friend, but in almost all scenarios it is a creative personal expression of who he has become. It is sometimes implied that it came from his parents who died (or went missing) when he was a baby; in so many cases, engineering education is more inherited in comics than it is taught.

The most recent *Space Jam* (Lee, 2021) suggests that the technical ability to express oneself by creating games may be similarly genetic.

The character who plays the son of LeBron James creates a video-game so powerful that it has the potential to imprison all human life on earth, but he could not be more excited to go to a basic game design camp where he will presumably learn . . . something? (Both of us have taught related material, but our students' games have only rarely ended all life on earth; it is not on any current syllabus.)

The metaphor of creativity being something inherent or innate rather than taught pervades almost all popular cultures' experience with it. Teachers, per Illich (1971), exist as foils to institutionalize creativity rather than support it. No matter whether it is in the past, future, or present, schools are typically represented by bored students munching on a pencil, listening to a lecture. Even in *Big Hero 6*, which presents situations in which people learn through experience, tinkering, and project-based learning, the protagonist learns only incidentally from anyone except for himself. He is given the resources to learn but no guidance that is not explicitly nefarious.

In *Big Hero 6*, as well as Spider-Man comics and movies, data on creative engineering design are neither collected nor shared. It is a trope that stealing the product of a student's design experience—e.g., webshooters—would unlock untold unfortunate possibilities. Those may be obvious McGuffins, but it remains true that most speculative fiction does not imagine a world in which so much as an engineering notebook is kept.

Star Wars is one notable exception, as everyone is learning to fix their constantly failing ships. Although there does not seem to be any school where one can learn to be a mechanic, everyone nevertheless learns how to create, modify, and adapt ship technologies (presumably at the risk of dying in the vacuum of space, though that happens remarkably rarely in this fictional universe). It is consistent with the *Star Wars* imperial dystopia that the purchase of ships is the purview of the elites and that everyone else must learn to work on technology. Small children are expected to be able to build their own droids without outside instruction, and, indeed, are not expected to

have any meaningful amount of instruction. Only the Jedi Academy and the Imperial Academy are mentioned, more or less, as schools, and they are both framed as propagandists. In an odd turnabout, the Imperial Academy is a purely voluntary device for (predominantly white, human) children to become imperial officers, and the Jedi Academy takes children from their parents permanently. In *Star Wars*, educational institutions are propaganda, but technical apprenticeship learning is crucial and good. Due perhaps to the lack of education, data are effectively freely accessible, often wrong, and subject to no security. Secrets are encoded, but always decodable; whether good or evil, the entire galaxy is sort of a “move fast, break things” hackers’ dreamscape.

The Marvel and *Star Wars* universes assume the classically hierarchical position that one either has innate ability or will exhibit total incompetence. What is to be done about a future where people learn only on the job or in times of great need? Is institutional education inherently a counterpoint to engineering education?

Toward Just Futures: Creative Data

The good news is that much of what is so valuable about making practices and creativity is the ways it can emphasize tactility, systems thinking, and literally getting our hands and limbs *dirty* in the complexity in front of us. If some of the problems with democracy, safety, and individual expression are the limitations of the digital platforms and digital tools at hand right now, then the focus here on analog making feels like one pathway forward.

What are the frameworks in which creativity can be sold to formal or informal learning spaces as educational? What are the forms that feel “schoolish” enough to be treated as first-class citizens by schools? For instance, programming computers makes a lot of sense to school administrators as an academic subject; therefore,

programming games can fit in schools. However, programming, say, the hairstyles mentioned earlier (Eglash et al., 2021) is a harder sell, even if it is every bit as complicated and potentially more useful than programming yet another quiz game. Because of the formalist requirements of technological creativity, often the expressive element can get lost. In painting class, are students allowed to paint what feels meaningful to them, or do all students paint still-lives for the entire year?

This question perhaps points us back to Illich on one side with most of current educational research on the other side. Illich (1971), among many others, shows that the institutionalism of the school exists to legitimize itself. Because society is itself racist, sexist, and biased against the agency of children, and because schools must justify themselves to that society, only by explicitly rejecting institutionalism can we enable kids to create things that are meaningful to them. In other words, it would only be educational to enable kids to create if it didn't "feel" educational. Illich is effectively suggesting (at least in modern contexts) that the creation of expressive solutions to personal problems is an inherently good thing. Another critique (from, e.g., Warren et al., 2020) is that by focusing on creative technologies we are enabling a neoliberal, hyper-Western, technocentric perspective on what education means and is. Learning equitable community values is perhaps more important than personal expression; it may be, at least, a crucial prerequisite for responsible personal expression. Obviously, they can coexist, but they can also directly conflict. boyd (2014) shows how memes and media generated by young people can be clearly personal expressions of values while manifestly entrenched in reactionary models of power and truth (e.g., white supremacy, incel culture).

Perhaps ironically, this potential for technocentrism is often incompatible with (or at least not amenable to) surveillance capitalism. Despite generating reams of data (artifacts, physical tools, digital production) in almost every maker project, there is very little work

on using those data either for selling to corporations or for improving student experiences. One counterexample—GitHub Copilot (GitHub, 2022)—uses the data of the millions of source-code repositories to generate live “boilerplate code” for new projects. It is an unquestionably neat gimmick: someone could write a working program with clever seed words and a liberal use of the Tab key. Similarly, though research projects (including ones conducted by the authors) have used student-generated data of this type to help those students in live teaching contacts, it remains extremely uncommon to see a product that adopts this approach in public schools. It is surprising enough that it raises the question “why”? Potential answers vary: the data is too noisy; the outcomes vary too much; creative work is too hard to categorize. The problem likely results from a metaphor mismatch. If students are being asked to be “original” and “creative,” they may not like to think of their work as data, which can feel either anonymizing or institutionalizing.

Perhaps unsurprisingly, we are landing on the perspective that making and creative education have vast potential to disrupt potentially harmful modes of both pedagogy and data analysis while embracing explicitly antiracist and justice-oriented perspectives—though not without a passel of potential pitfalls. In the conclusion to this book, we will try to compress all of this into specific, actionable suggestions.

Interlude: Making

The story of this interlude is the story of a battle lost (or at best drawn) against technocentrism. This interlude was started with the intention of coming up with the simplest possible Python example in which a reader could explore what they like about their creation and try out automatic music generation. What it became was a code sample in which a beat is generated that is reasonably interesting, quite easy to explain, and endlessly fiddleable. Is it: a trap; a starting point; a generative worked example; or are we just justifying interesting code with rhetoric? (This is always a danger.)

For the last interlude in this book, we *do not* start with the importing of libraries, exactly, but rather with the installation of new software. In this case, sound libraries are required. Do not get too caught up in why this is not in Python by default: it often is, but this specific platform is not typically intended for music. For now, ignore the streams of nonsense-looking output that may result from software installation. These are noteworthy considerations around data use and reproduction but are beyond the scope of the lesson offered here.

```
!apt install fluidsynth # this is the library that the computer needs to generate
sound
!git clone https://github.com/nwhitehead/pyfluidsynth # this connects it to
Python
!python ./pyfluidsynth/setup.py install # this installs the downloaded python
connector
Reading package lists ... Done
Building dependency tree
Reading state information ... Done
<... a bunch of nonsense ...>
Finished processing dependencies for pyFluidSynth==1.3.1
```

Now we get to import our libraries!

```
from IPython.display import Audio # this lets us play music in the cell
from pyfluidsynth import fluidsynth # this is the Python connector we installed
above
import numpy as np # our data analysis library
from random import random, randint, choice # random numbers
```

Contained in the next box is the entirety of our music generation software. It is short! You can do this!

There are arguments in a couple directions here: this might seem daunting, confusing, or exclusionary; it could just as easily feel exploratory, freeing, or revelatory. Creative work can often be like that. Questions remain (as throughout the book): What might we expect you to know or not know? What might we expect a student to know or not know? How does code like this interplay with identity? To what extent is this likely to feel like it is off-putting and to what extent is this an entry to seeing that anyone can do creative work like this? Confidence—perhaps self-efficacy—is needed, but the musical knowledge required is almost nil. For example, you might look at the code below and decide that you do not know why E minor consists

of those numbers. I (Matthew) have no idea why E minor consists of those numbers, but that does not bother me; I know relatively little about music theory, so I just looked it up. Knowing that I can just look it up—and knowing that and knowing who I could ask for help—is more of the creative block here than “not knowing,” but resources and power are inequitably distributed.

In short, make some music by fiddling with the following numbers. It really is fun, and it would be surprising if there was not some music made with some instrument accessible from this code was not pleasing to every single person who could read this. Who knows?

```
fl = fluidsynth.Synth()
fl.start()

# the arcane location just below is where the sound software put the
# “sound fonts” - that is, the libraries of instrument sounds by note
sfid = fl.sfload(“/usr/share/sounds/sf2/FluidR3_GM.sf2”)

# you can mess with this! change the key!

piano_e_minor_notes = [0, 64, 66, 67, 69, 71, 72, 74]

# this is just “blank” and “bass drum” but many other drums exist!
drum_bassdrum_notes = [0, 47]

# 4 on the flour. 16th notes
seqlen = 16

# track (“program”) 0 is drums
fl.program_select(0, sfid, 128, 0)

# track 1 is piano
fl.program_select(1, sfid, 0, 0)

s = np.array([])
seconds = 0.07 # how long is a 16th note?

# each of these just selects from the lists above
# either silence or the notes we put in that list
drum_riff = [choice(drum_bassdrum_notes) for _ in range(seqlen)]
piano_riff = [choice(piano_e_minor_notes) for _ in range(seqlen)]
```

```

for i in range(seqlen * 4): # repeat the riff 4 times so it sounds riffy

    drum_note = drum_riff[i % len(drum_riff)] # play the right note
    # the "%" means "mod" - mod is "integer remainder" - like, 4% 3 = 1
    # we do that so we can go around and around a list of the right size
    if 0 != drum_note: # if not silence
        fl.noteon(0,drum_note,20)

    piano_note = piano_riff[i%len(piano_riff)] # same idea as the drums
    if 0 != piano_note:
        fl.noteon(1,piano_note,20)

    s = np.append(s, fl.get_samples(int(44100 * seconds)))
    # just tack the notes on the end

fl.delete() # ok, let's play!

framerate = 44100 # this is what our player expects, like a CD
Audio(s, rate=framerate, autoplay=True) # and let us hear the riff

```

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Conclusions and Reimaginings

As we begin our approach toward the final landing place for this volume, let's take a look at this book from the 30,000-foot level: we're in a small Cessna jittering across the sky and the words and code and tangents are splattered like Pollock-rejects across the canvas of the earth. From here, the book's logic might look even clearer than when you're in the eye-level depths of AnSpec sludge. Let's see what's around.

If we map the terrain of this book, we have admittedly dawdled across the familiar contexts of expected learning spaces. Assuming that you first ventured through the introduction of this book, the organization of this book's chapters should not be all that surprising.

The explorations of formal schooling environments, of libraries, of gaming domains, makerspaces: these are all par for the course of what educational researchers in the twenty-first century *should* attend to. Sure, you might be a little sick of the sci-fi references or might quibble with the Python examples, but we hope that this book's approach should be familiar to an educational research audience.

Considering that this book generally covers the terrain of most educational research books might cover, we want to present an opportunity for a grand critique of the book itself. We encourage you to feel unfulfilled as you reach the end of this book. Is this it? The

future of data, design, and justice, and we are still confined to the same basic premises of schooling, of assessment, and of how data are or are not included within these systems?

The pragmatists in us have been sitting in the writing cockpit for too long, and we are ejecting them for the final pages of this book. We are writing at the scale of widespread freedom and momentarily ask you to let your penchant for practicality parachute down to earth on its own (it will be waiting for you safely when we're done here).

If you have been wading through the overlapping contexts of harm and institutionalized repression in schooling and informal learning structures across our recent past, then you know that the pragmatic steering toward fixed destinations of assessment and progress have not staunched the wounds to individuals' safety, to democratic structures, or to collective societal repair. Ours is a moment that is pregnant with far too many existential crises all competing for our very limited attention. You should feel *unsettled* in the way this book has hewed so closely to the existing systems of education. Frankly, we should be unsettled with this status quo across books, across systems of education, and across our collective endorsement of it writ large. Why have we made it so easy to box our entire field into a set of finite and unimaginative constraints? Can we divvy up learning so easily?

AnSpec, as an epistemological and axiological framework, should strike us all as a reminder of how reductive and harmful our field continues to be. When we can easily count where educational research lives and what it values, we can consider the boundaries we have imposed on ourselves. What does academic "achievement" mean if students are still expected to labor within conditions that cause harm to them, further stratify social classes, and erode the world's capacity to sustain us for much longer? Our focus on technocratic solutions to generations-long moral dilemmas has failed us as a field. No amount of bandwidth or pixels or RAM or data in general can lift the shroud of inequities that envelop us vis-à-vis capitalism, racism, and exploitation. If there is a kind of memory that might be leveraged

for transformation, it is a memory of an imagination that has been sapped from Western schooling and cultural practices.

In the spirit of the situationists who helped guide aspects of this work in chapter 5, we seek to twist the familiar threads of educational research into new knots and unravel those that have not been harboring good. We want to intentionally *deconstruct* not only the premise of this book but also of educational research and the role of data writ large.

Deconstruction as Pedagogy

The truth of the matter is that to move forward we must not rely on the technocratic and meritocratic assumptions that drive edtech as dominant forms of schooling interventions. Instead, we turn to everyone's favorite quippy poststructuralist, Jacques Derrida. Rather than advocate for a pure or essential form of data or of design or even of learning, we learn from Derrida (1978) that not only is there not a *true* form, but also that we must reject such positivist notions in our work and, yes, in AnSpec. Like the fundamental principles of philosophy that Derrida sought to redefine (or undefine), we must treat the frameworks here—of AnSpec and of guidance for design—“as tools which can still be used. No longer is any truth value attributed to them; there is a readiness to abandon them, if necessary, should other instruments appear more useful” (Derrida, 1978, p. 284).

This deconstructionist bent is not about simply putting our hands up and saying that, if linear definitions do not comfortably fit the myriad forms and desires of the living world, we must give up. On the contrary: we are offering the tools of AnSpec in this book, as flawed as they may be, as malleable to the needs and conditions of lived and constantly mutating life. We must fold these processes back into the rich loam of educational and policy discourse, nudge our

field ever further out of a system that is comfortable in using common metrics to measure individuals against. The ideas here and in educational research in general must be “employed to destroy the old machinery to which they belong and of which they themselves as pieces” (Derrida, 1978, p. 201).

So, cautiously allowing the pragmatists to rejoin us in this conversation about deconstruction, data, and pedagogy, let us consider the ways we might need to upend existing practices and research approaches while still hoping to remain gainfully employed under the current contexts of Western teaching institutions. From within classrooms, we might intentionally critique the forms of data development and leverage an AnSpec framework as a pedagogical tool. Discussing with young people of all ages the role of data as it imposes on their lives might reveal the myopic focus on singular characteristics and the ways in which such assessment-guided bluster drops us into predetermined and harmful categories.

We are asking researchers to keep their feet planted firmly in a terrain that works both critically and expansively across the varied domains of AnSpec. This includes, first, utilizing myriad forms of robust and humanizing research practices that best affirm the ingenuity and possibilities proliferating in our varied learning environments today. It also means simultaneously seeking to work beyond a world in which data might be categorized by tools of individuality and by metrics of being known or not known by state-funded tools that surveil, harm, and suppress. The data-induced dysphoria of these contrasting demands is substantial. But rather than slowly boil in the world as it is, we can craft something new.

Propositions for a New Educational Data (Dis)order

Books take a long time to write (unless you happen to be Joyce Carol Oates). In the years we have taken to write and subsequently revise

this book, new continents of data exploration have been discovered, pillaged, and discarded. The technocratic cycle of capitalism is a rapid one.

Indelible in our memories is the fomented optimism amidst uncertainty and fear during the prolonged and ineffective national response to the COVID-19 pandemic. A focus on distant and hybrid forms of schooling shaped much of the first year of the pandemic to a widespread consideration of attention, the use of cameras, and the understanding of the limitations of facial recognition in a society of masked individuals (for surveillance as well as to unlock our phones). We might have rubber-banded back to a norm of adult-centered forms of authority and power in schooling since the pandemic and, while the jury is still out, our relationship to data vis-à-vis the pandemic has largely remained the same. The tools for *collecting* data beget that data collection. Statistics about logging on, about staying present in online spaces, and about student achievement have only become greater part of an increasing hysteria about learning loss in a world where more than a million individual lives have succumbed to a wireless and viral pandemic. Which data matter and to whom?

Similarly, though dire on a more existential front, the advance of machine-automated image and text generation and artificial intelligence (AI) presently threatens familiar forms of schooling and learning. What does it mean to learn to code (or even use the examples in this book) when you can use plain (but still “standard”) English to have an online tool write and create computer scripts for you? Why should you write an essay about the role of data and privacy in an undergraduate ethics course when this same tool can probably guarantee you at least a B-level version of the same in seconds?

The hand-wringing about schools, teaching, and AI focuses on tools as shortcuts to labor but not shortcuts to critical thinking, empathy, or joy. Dall-E 2, OpenAI’s image-generating tool, has been a source of frequent delight for Antero’s kids (we refrain from saying “constant” delight here as “credits” limit the frequency with which

we use it). Typing in images their then three-year-old's heart desires to see has been a magical process that traditional photos online cannot produce: anteaters eating tacos; anteaters eating tacos in a pool; anteaters sitting at a desk watching a show about tacos; an anteater riding a blue bicycle and wearing yellow shoes; and so on. (Anteaters and tacos turn out to be pretty popular in the Garcia household.) Like any other toy we might use in moderation with our kids, AI might be a tool to harness for play. It might also whack our learning practices into new terrain. That too is part and parcel of the nature of a society that does not stay still. The antsy-ness that we see in the adolescent forms of twenty-first-century pedagogy is also a dissatisfaction with twenty-first-century forms of injustice cloaked in schooling and data. Throughout this book, we have explored data, justice, and creative play in education. It would be so convenient to tie everything up and come to a sentence-long conclusion. But Derrida won't let us.

When we submitted a few chapters of this book to the publisher, one of the criticisms made (by a very good and helpful reviewer) was that the book was too “flip”: that serious issues should not be enjoyable to read—that is, they are serious and should be taken seriously. Respectfully, that tradeoff speaks to the book itself. What is rigorous? What is serious? How can you deal with the lived realities of oppression and authoritarianism and oligarchy in a way that would be most helpful to people without angering them? It is unlikely that there is a single answer, but the argument that classically “academic” writing (perhaps using classical analyses to follow classical rhetoric) is the only way to take serious issues seriously seems to be the same fallacy that underpins misbehavior with data and authoritarian pedagogies. Not everyone is working in good faith and not everyone is amenable to systematic empirical arguments or solid theoretical perspectives. Arguments must adapt, whether we like it or not, and that adaptation will require data, a focus on acting justly, and probably a bit of blind hope . . . whether we like it or not.

This book is one long conclusion; we have made it hard on ourselves. Most books in the field keep it tight or go broad—better options, both—but we have tried to thread a needle with a haystack. Plainly, we hope that every reader can now look critically at the intersections among data, education, justice, and play. We think they might also be able to explore learning analytics, make beats, and recontextualize Ivan Illich in modern schooling.

We are but voices voiceless on a page, and we cannot make you do anything. Learning is hard; books hold no control. A senior faculty member—an expert in theories of pedagogy—once told Matthew that a new perspective on an old phenomenon is among the most powerful gifts of good pedagogy. This book is overfull of perspectives. How do you take these perspectives and use them in your life, classroom, museum, after-school club, with your kids, or with your parents?

To close this book, we offer five propositions for how we design for deconstruction, (dis)order, and possibility. These are propositions that we hope are self-evident at this point and useful to young people, teachers, researchers, policymakers, and any other individuals and communities willing to put into practice the principles that move us from dreaming to building *through* dreaming. We ask you to dream-build with us:

- 1. Look at the specifics of how identity is encoded; encode identities in ways that are explicitly antiracist, antisexist, and prosocial.**

If you cannot articulate how an identity is encoded, it is probably encoded in a problematic way. Does your automatic faucet work 80 percent of the time? Whose attempts lie in the 20 percent faucet-failure category, and how does the simple math of an automatic faucet implicitly encode identity? The process through which we must consider a “racist soap dispenser” is not a labyrinthine one (Plenke, 2015). It involves simple design aspects overlooked and diverse perspectives absent in the creation and iteration process.

If you are not explicit about how you think about race, gender, and bias in your system—whether in rules, law, program code, or otherwise—it is going to encode the hegemonic structures implicit in whatever data you are using. We started this book with descriptions of how schools are pressured to substitute test scores for human caring; that is only one example among millions of ways that data implicitly encodes injustice. In our final chapters, we (hopefully) made generative suggestions on how we might combat that injustice. Chang-Bacon (2022) suggests the term “race evasiveness” for the discomfort that (for example) white engineers, teachers, and designers have in specifically saying “we need to explicitly make sure that this faucet is not anti-Black.” Implicitly coding identity in statistics is an implicit form of race evasiveness.

2. Find the surprising and creative; enable people to break the system.

Learning is creative; you cannot learn to understand something without trying to do something with it. If content is generated and governed only by the teacher or facilitator and no “handles” exist for learners to create something that is meaningful—or at least culturally relevant—to them, then you should evaluate whether it is a learning environment or simply a mechanism of control.

3. Malicious compliance is at the heart of good pedagogy; find and amplify points of resistance and friction.

There is a contradiction at the heart of pedagogy between authority and respect. Apple (2004) identified it as the fundamental conflict between capitalism and education; if the teacher is the boss, then the students should necessarily have little say. Again, using Apple as a guide here, what is important is how you—whatever your role is—enable students to organize against inequity, against racism, in solidarity. This is the power of education even if schools are loci of capitalist ideologies (so are factories, perhaps, but that is where you will find a union to join). Illich’s vision, despite antitechnocratic intention and

with only 20/20 hindsight, can be (mis-)read as a defense of a techno-libertarian dystopia. From where do we get the next Illich, or is the lesson that there should not be one?

4. Perceive assessment as control; decide why, when, and how you evaluate and assess.

Assessment is the tail that wags the dog. Two just possibilities for conscious interaction among assessment, data, and privacy exist: obfuscate assessment or make just measures. Obfuscating assessment is merely delay: structures of control will catch up with individual dissent, but a perennial truth of education is that students are different every semester, every year, and standards change almost as quickly. Teachers rarely remain in the job more than a few years. Assessment that *works* will be valued, even if it is not assessment that works the ways that the administration wants it to work.

5. Embed respect for people and context; everything at every level is cultural, social, and connected, and nothing is individual.

Designing requires appending meaning from one component or phenomenon or individual or system to another. It is a delicate balance of networking and “knotworking” (Engeström, 2008). Don’t forget, however, that tangled in these webs of design and data and learning are *communities*. People and our cultures and our love are bound up in the systems powered up in our scholarship.

We invite you to design boldly, loudly, and without the pragmatist always driving every decision. We often sacrifice the liberatory in search of the pragmatic. We settle for dehumanizing because the alternatives require that we do the groundwork of collaboration, organization, and action. Our scholarly pursuits of justice cannot sit idle as we sleight-of-hand a definition of *equity* from one palm to the next. We must work toward iteratively adapting and dismantling new frameworks as we step from the present moment into the future.

Notes

Chapter 2

1. Hill (2012) provided a story in which a teen was identified as pregnant before her parents knew. Perhaps humorously, a data scientist at Facebook (Fraser, 2020) wrote a rebuttal eight years later about how this was neither representative nor, if it was true, a particularly bad thing.
2. Berland (2015) goes into more depth on data and design using this example.
3. <https://twitter.com/censusAmericans/status/1284956186366836741>

Chapter 6

1. Scratch is the predominant programming language for younger children world-wide (Resnick et al., 2009).
2. Intelligent libraries always turn evil, according to *Star Trek* itself (Kelly & Zurek, 2021).

Chapter 8

1. Note to the reader: A hand turkey is not a canonical example of principled maker education (but it is also not *not* maker education).

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